Gamification for Heating Solutions

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Summary

The report is concerned with design of gamification model that would collect user feedback for use in heating and cooling system. The main incentive to the participants is energy efficiency resulting in smaller bills, however the model should consider other elements. There are different preferences of thermal comfort in apartments, financial goals and environmental awareness among apartment owners. The gamification model is not focused on one goal, e.g. energy efficiency, rather should reward being interactive and the willingness to support preferences set by the majority in the community.

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1 Introduction

1.1 Background

Fortum is an international energy company, providing electricity and heating solutions. They are a leader in clean energy solutions and provide solutions to help customers lower their carbon emissions.

One aspect of their business is to provide heating solutions for residential buildings. With this in mind, Fortum would like to develop a way of reducing energy consumption within buildings by encouraging tenants to keep their flats at an optimal temperature. As a secondary aim, they are also interested in a solution that would allow the collection of feedback to determine the comfort level of tenants. Since heat usage of an individual flat is impacted by the actions of users, it is important that this solution appeals to the large majority of users.

Given this set up, the suggestion is to use insight from gamification theory; that is the application of game-like mechanisms outside of a game situation. Examples include loyalty schemes for supermarket customers, such as the famous Biendronka craze, fitbits which promote active lifestyles, and social media 'contests' to engage more users [17].

In particular, Fortum are keen to develop a solution which not only ensures optimal temperature usage, but ensures customer engagement, comfort and knowledge. They also hope to target demographics of user with their solution, for example over 65s.

1.2 Report contributions

The report makes the follow contributions

- We set out a model for using gamification techinques to determine an optimal strategy for achieving the aims of the company.
- We provide a summary of the key concepts of gamification that will be useful in developing their solution.
- We present mathematical models of aspects of the gamification process, in particular reward design and demographic targeting.
- We finish with some suggestions and ideas for practical implementations of a solution.

1.3 Assumptions

The following assumptions are important in helping us formulate the problem clearly:

- We assume that Fortum is able to meet all concerns around demand and pricing, such the user alone is able to control the temperature of their flat.
- We assume there is at least one thermal sensor in every flat.
- We assume that there is a strong enough positive correlation between individual user behaviour and overall heating and cooling performance, to justify the use of control at the level of an individual to contribute towards a target for the whole building. This assumption is important; if it were to not hold, then having only a few users not actively engaging with the solution could still lead to no improvement in the overall heating usage.
- We assume that we have some model for how to set optimal temperature for each user.

2 Problem formulation

We consider the problem within the context of control theory; that is, given an *objective function* that describes some quantity we wish to maximise, we seek implement controls that minimise this objective. *Gamification*, the process of applying game-like mechanics to non-game situations, is one such method for determining these controls.

2.1 Objective function

As outlined in Section 1, the objective should take into account deviation from optimal temperature, user engagement, and user knowledge.

We want to maximise the following objective, V at time t:

$$V_t = \mathbb{E}(\alpha_A A^U + \alpha_K K^U - \alpha_T T^U) \tag{1}$$

where $\mathbb{E}$ is the expected value, A is the number of active or engaged users, K is the knowledge level of the users T is the deviation from optimal temperature and $\alpha_A, \alpha_K, \alpha_T$ incorporate our assumptions about the relative importance of each of the terms. Each of these terms is some function of a control mechanism, U.

To determine A, we could calculate the deviation from the optimal temperature, T_{opt} using for example the squared l_2 norm of the difference in actual temperature T_i of all N users, given by

$$T = \sum_{i}^{N} (T_i - T_{opt})^2. \tag{2}$$

We seek to determine the controls U that maximise the objective. There is also space for some *feedback*, from the controls in determining the optimal temperature T_{opt} although we do not explore this in detail here.

2.2 Determining controls using gamification theory

We need to determine the controls U that maximise the objective. One method for controlling this system is the approach of gamification theory. In this section, we summarize some key aspects of gamification theory [10], [16] and [18].

Gamification is the concept of applying game-like mechanics outside of a game context. It has been used successfully in a range of areas such as business, crowd sourcing and public health.

Frequently, $\boxed{\text{rewards}}$ are awarded based on $\boxed{\text{progress}}$, the completion of tasks that helps achieve a wider objective. Different systems for reward include points, prizes or badges. A key principle of gamification theory is that maintaining *flow*[9] leads to increased engagement; the experience many have of virtual gaming.

Definition 2.1 (Gaming Loop). The process by which a user remains hooked into a 'game'.

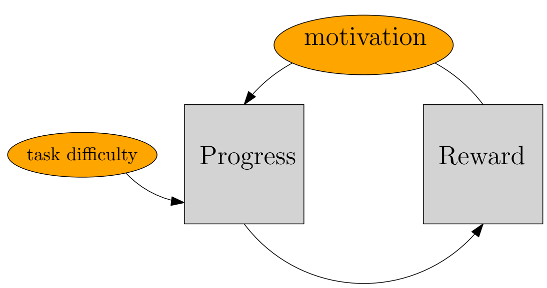

Figure 1: The Gaming loop

To use gamification effectively, it is important to determine how what forms of $\boxed{\text{progress}}$ should be rewarded to help obtain the objective. In addition, there is a question of how $\boxed{\text{reward}}$ should be allocating to maintain engagement. Engagement is a measure of how much the user is participating in the progress section, completing tasks, interacting with the system, giving feedback. It is linked to the $\boxed{\text{motivation}}$ of a user, which is a quantity describing how likely the user is to keep up their engagement. By changing the system design, we can impact a users motivation and therefore increase engagement.

The following two dynamics are also important to consider when relating the gamification process to the intended outcome.

- A common feature of successful gamification systems is the front-loading of reward schemes; that is early on in the game tasks should be easy and reward high.
- By contrast, $\boxed{\text{task difficulty}}$ should increase over to keep more skilled and experienced users challenged.
- It is important to vary the game dynamic. This could come in the form of elements of randomness such as special bonuses, or varying level of difficulty of tasks.
- The $\boxed{\text{behaviour of other users}}$ influences other users. This might be through allowing 'high achievers' to encourage the medium achiever, for example allowing them to become part of teaching or mentoring schemes.
- Users can be influenced by $\boxed{\text{non-user behaviour}}$, i.e. consider the example where a tenant has a child or grandchild that doesn't influence the progress, but is targeted by a reward. This is akin to the method employed by the Polish supermarket chain Biedronka which offers toys as part of loyalty schemes; parents collect stickers by exceeding some levels of money spend on shopping, and these can be exchanged them for stuffed toy vegetables.

In Section 3 we consider models for the reward system. In Section 6, we outline some practical suggestions for the implementation of a solution, based on applying gamification concepts.

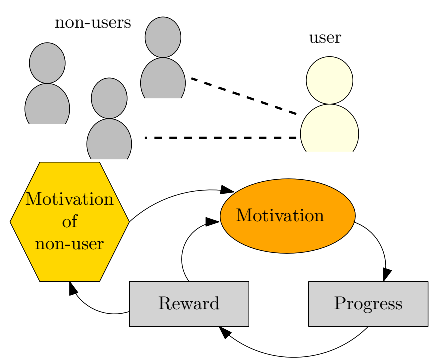

Figure 2: Non-users can also influence the progress of a user

3 Reward value function

As outlined in Section 2.2, determining how to reward progress is an important step in maintaining engagement.

In this section we assume that reward is allocated at discrete time steps for progress in a finite number of tasks. At each time step, the total reward is the sum over all tasks of the reward earned for each task.

The reward function should depend, among other things, on the progress made towards particular tasks, the difficulty of the tasks and some user calibration.

In this section, we suggest some approaches for quantifying these variables; specifically a method for calculating the progress score for the specific task of staying within an optimal temperature, and user calibration in terms of a time weighting function, which favours early users in order to encourage engagement at an early stage.

3.1 Fuzzy set approach to modelling the reward function

We propose a model for assigning a progress score for the specific task of maintaining optimal temperature. The task of staying at an optimal temperature range could be assessed as simply pass or fail. Alternatively, we might want a smoother way to assess progress, ascribing more reward to those who are closer to optimal. To do this, we consider using fuzzy sets [19].

A fuzzy number is a quantity whose value is imprecise, rather than exact as is the case with "ordinary" (single-valued) numbers. Any fuzzy number can be thought of as a function whose domain is a specified set. Each numerical value in the domain is assigned a specific "grade of membership" where 0 represents the smallest possible grade, and 100 is the largest possible grade.

For example, if the optimal temperature is 21 degrees, then the fuzzy number 21 can be described as a set, e.g. {12 ... 30}.

Now the task is to find an appropriate membership function, μ to describe whether a given temperature belongs to the fuzzy number set for the optimal temperature. We propose a function that based on the normal distribution $N(m, s)$, where the mean is the optimal temperature and the standard deviation s is a parameter that will be used to fine-tune the reward function to the requirements of the game. The standard deviation is a measure of variability. It defines the width of the normal distribution, or in other words far away from the mean the values tend to fall. The value of the density function for $N(m, s)$ and for

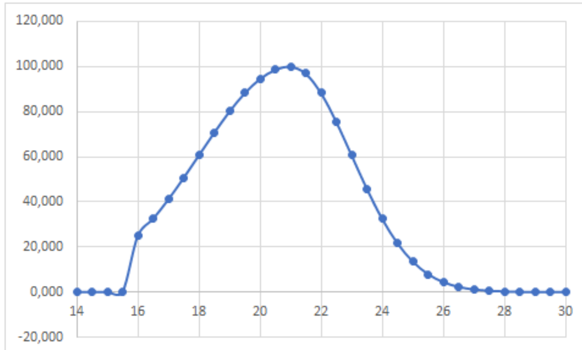

Figure 3: An exemplary reward function.

temperature t will be denoted by $f_{m,s}(t)$.

In the context of assessing progress for temperature maintenance, we may well want to consider rewarding temperatures below the optimal less that temperatures above the optimal. To obtain this asymmetry the two normal distributions $N(m, s_l)$ and $N(m, s_r)$ are used to model the left side and the right side of the function, respectively.

Let us take $m = 21, s_l = 3, s_r = 2$. This means that the optimal temperature is on level 21, the range from 18 to 21 is 'normal' on the left side, while on the right side the range from 21 to 23 is 'normal'.

Let assume that the reward for maintaining optimal temperature is M points e.g. 100, every deviation from this point lowers the reward. It is possible to give the reward equal to zero. Then $\mu(t) = \frac{f_{21,3}(t) \cdot 100}{f_{21,3}(21)}$ for $t \in [16; 21]$, $\mu(t) = \frac{f_{21,2}(t) \cdot 100}{f_{21,2}(21)}$ for $t \in [21; 28]$, and 0, otherwise. We plot the example progress estimation in Figure 3

To be more flexible we can extend the set of parameters with a time interval T, for which the given function works. The parameter T can be used to describe night or day, some special hours etc. Manipulating the parameters, we are able to take into account some other aspects of the game. For example,

- personalization to distinguish between different comfort levels ('lizards' vs 'mammoths') can be made by slight changing of the optimal temperature m,
- personalization to distinguish between 'night owls' and 'morning larks' can be made by setting the parameter T and slight changing of the optimal temperature m,
- to force people to not overheating we can lower the s_r parameter.

3.2 Time dependence

In many successful gamification examples, reward is higher earlier on in a game. This encourages users to become hooked in and encourages them to keep playing. Hence we want to inflate the reward for new users. The advantages and disadvantages of the reward-based gamification systems are presented in [18] and [12].

Image we have some calculation r_k of the reward earned from completing task k at time t without any inflation. Then we can calculate the weighted reward as

$$r_k^{\omega} = \gamma(t) r_k. \tag{3}$$

In Figure 4 we depict a suggested profile for how γ might change with t; initial inflation is large, decreasing over time until eventually become roughly constant, at a time that should coincide with the users adoption of the system. For example, we could take $\gamma = Ae^{-Bt} + C$ for some constants A,B and C, parameters to be determined by prototype testing.

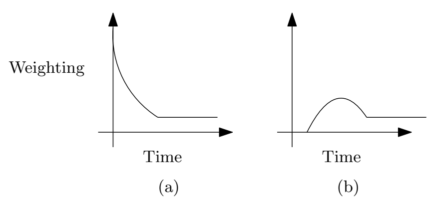

Figure 4: Time weighting functions, $\gamma(t)$ for different priority tasks (a) engagement (b) learned behaviour

We may also want to consider changing this weighting depending on the task. For example, we may only want to focus on rewarding simpler or more educational tasks early on, such as giving feedback, encouraging users to engage with the process before being put off by more challenging tasks such as maintaining an optimal temperature. To do this we determine an inflation function for each task. We can then obtain the total reward as the sum of the rewards earned over all tasks.

$$\text{reward(t)} = \sum_k \gamma_k(t) r_k \ . \tag{4}$$

As an example, we might wish to not count reward for the task of maintaining the optimal temperature until the user was engaged. In this case, the form for γ would be modelled instead as initially zero, then increasing slowly over time to gradually introduce the new task until decreasing again past the adoption stage. This would also allow a training period where the target temperature was set.

4 Interplay between reward type and user dynamics

In the previous section we outlined a strategy for determining reward as a function of known data from an individual. We now consider a model for determining the optimal reward scheme based on user characteristics, which requires a model for user behaviour.

We outline a general model for predicting the behaviour of a set of rewards, followed by a simplified version that allows the evaluation of a model based on how well it caters to different user characteristics. In Section 6, we outline research into the types of rewards and characteristics that should be considered when designing a gamification system.

4.1 General Model

We consider individual users, $\mathbf{x}_i$ associated with different characteristics, $\mathbf{y}_j$. For example, some users may demonstrate more competitive tendencies, others may be more materialistic or higher risk takers. This segmentation of users is often referred to as *user taxonomy*, see for example [7]. We also have a set of reward types, such as leadership rankings, coupons, or progress bars. Different rewards will cater to these different individuals in different ways. The resulting impact of reward on motivation can be used to determine motivation levels.

We propose the following approach for modelling the change in motivation over time:

- We determine a strategy for providing reward as a function of progress.
- We model the motivation factor as a function of how well the rewards cater to the individual characteristics.
- We model task difficulty as a constant with respect to the individual. This is equivalent to assuming that calibration between difficulty and skill level is perfect and neglecting the impact that varying skill has on motivation. The latter notion could be introduced at a later date, allowing for the difficultly level to be drawn from its own probability distribution.
- We model progress as a function of motivation and difficulty level of different activities.

4.2 Simplified Model

We consider a user with characteristics $\mathbf{y}$, where $y_j \in [0,1]$ denotes the strength with which a characteristic is expressed by the individual. We denote by α_c the impact that rewards have on users with characteristic c, assuming this is time independent and no new rewards are destroyed or created. Assuming that rewards are awarded at discrete time intervals, and that the intervals between rewards are small enough that we can approximate quantities of interest as piece-wise constant functions between these intervals, we denote by m_t the motivation at time t, d_t, the difficulty of the task at time t, p_t, the progress made between time t and $t+1$, r_t the reward. We assume to fixed in advance value for d_t and then consider the following methods for updating the motivation:

$$\begin{aligned}
&p_{t+1} = m_t \times d_t \\
&r_{t+1} = p_t \times d_t = m_t \\
&m_{t+1} = m_t \textstyle\sum_c y_c \alpha_c
\end{aligned} \tag{5}$$

Hence, the probability of motivation drop-off in the long term is under this model entirely controlled by whether $\sum_c y_c \alpha_c > 1$. In order to sustain a healthy level of motivation, we see that this value should be greater than 1 for a high proportion of users.

5 Modelling a reward system that targets individuals outside of the network

We consider how we might model the interplay of an external network with the gamification system.

In particular, we consider the case where rewards are targeted at individuals outside of the game structure in the sense that they aren't able to make progress on their own. For Fortum, this could be the model of targeting children whose parents or grandparents are the ones setting the temperature of the flat. Hence the motivation of a user becomes a function that depends on an external state (i.e. pressure applied by a child). Therefore we need to consider a model for the external state.

In this particular case, the motivation of a user is tied to the spread of a craze through a separate network. A similar concept was employed by LEGO who, despite almost going backrupt in 2004, were able reignite interest using films and videos of their brickwork toys. Likewise, the fast food retailed Macdonalds tailor their happy meal products based on recent releases of films and movies.

5.1 Model

We outline a model for the propogration of a craze through a network of two user groups. We have a network of social links, *edges*, between individuals, *nodes*. Each node is labelled as either a user or a non-user.

It is reasonable to assume use that intra-group links occur with higher probability than inter-group links (children are likely to have large numbers of friends but only a small number of parents/ grandparents). It might also be reasonable to assume that one group is more densely populated (in general children have a lot more interactions with those of their peer group). Therefore, we model links between users according to the following distinct probabilities

$$P(\text{link user } i \text{ and } j) = \begin{cases} \beta_n & \text{if i,j are non users} \\ \beta_u & \text{if i,j are users} \\ \beta_{nu} & \text{if only one of i,j is a user .} \end{cases} \tag{6}$$

In general, one might expect that $\beta_u < \beta_{un}$.

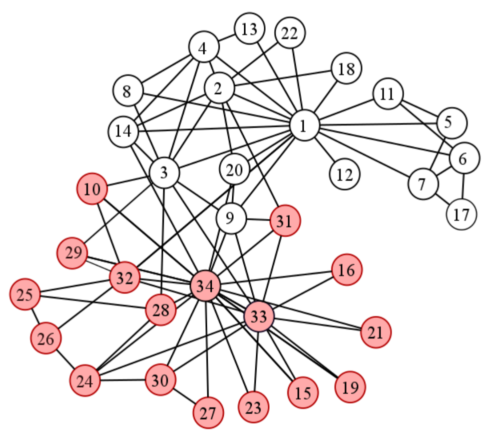

Figure 5: An example of a social network with two distinct groups, where links are more common in one group than another

We model can the propagation of a particular craze using concepts from disease transmission: initially a small number of users are 'infected'. At each time step, infected users infect those around them with a probability ρ_{infect}. They can also 'recover' (equivalently, lose interest in the craze), which occurs with probability $\rho_{recover}$. We consider a model in which ρ_{infect} depends on the type of neighbour. That is, non-users infect other non-users with probability ρ^{n}_{infect}, which is different to the probability ρ^{nu}_{infect} that they infect users, which is again different from the probability ρ^{u}_{infect} of users infecting other users. In the model, we assume that the probability of a user infecting a non user is zero; this assump-

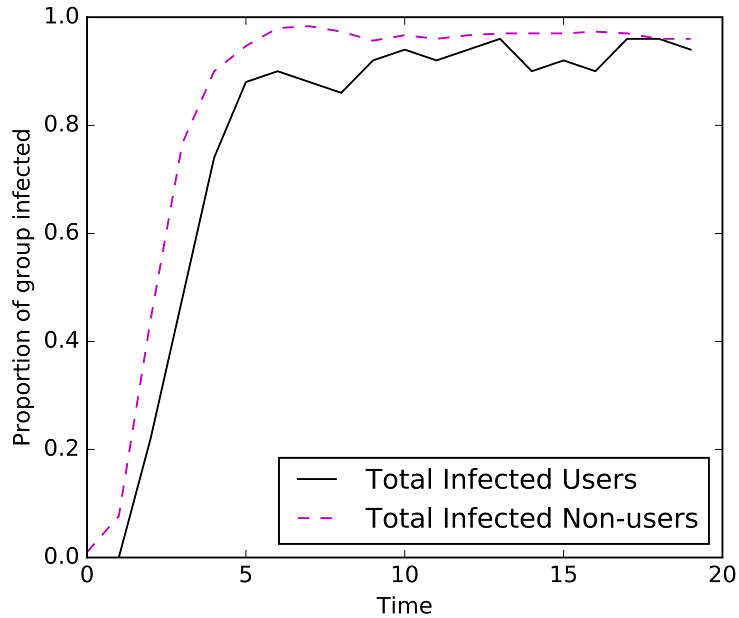

Figure 6: Spread of the craze through both networks over time

tion makes sense are we interested in modelling the user engagement not the engagement of non-users. However, the model can be easily adapted to include this effect.

We model the spread as a Markov process; at each time point, we can calculate the proportion of users who are adjacent to an infected node, or even the average number of connections a user has to infected nodes. The long term behaviour of this system will depend on the relative values of ρ_{infect} and $\rho_{recover}$, as well as the connectivity of the networks.

5.2 Numerical simulation

We consider a network of 50 users and 300 non users, with $\beta_u = 1/50$, $\beta_u = 1/\sqrt{30}$ and $\beta_{nu} = 1/25$.

For fixed values of ρ_{infect}, we can measure the record the number of infected users at a given time step. In Figure 6, we see the interplay between the state of the craze in the non-user population and the user population when $\rho^n_{infect} = 0.075$, $\rho^{nu}_{infect} = 0.075$ and $\rho^u_{infect} = 0.05$. In practice, you might expect non-users to influence each other with higher probabilities (in our problem, children might be more easily influenced by their peers than adults).

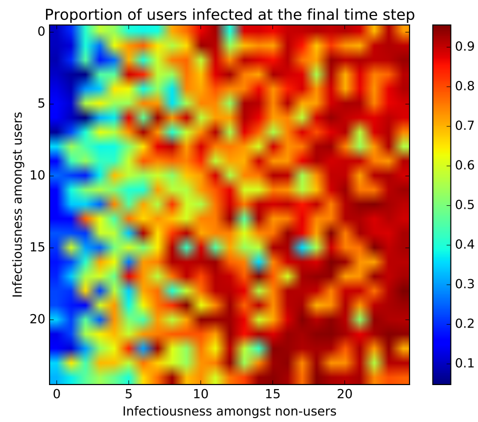

Figure 7: Effect of changing ρ_{infect} for a sparse user network

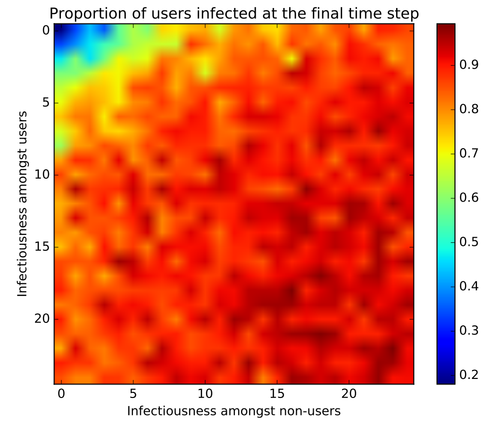

Figure 8: Effect of changing ρ_{infect} for a dense user network

In fact, the parameter ρ_{infect} is, to some extent, something that can be controlled by the designer of the gamification system. This is because they can control how appealing the reward is for a given group. Therefore, it is of interest to explore how changing this parameter influences the outcome. We consider different values of ρ^u_{infect} and ρ^n_{infect}, keeping ρ^{nu}_{infect} fixed as we assume this is something the game manufacturers are less easily able to influence. We consider two separate scenarios; one where the user network is dense and another where the user network is sparse. In Figure 5.2, we see that there is a clear dependence on the ρ_{infect} for the non-users when the user graph is sparsely connected. In the case where the user network is densely connected however, changing ρ^u_{infect} for non-users has an equivalent effect to changing ρ^n_{inject}, as can be seen in Figure 8, which is roughly symmetric along the diagonal. It is worth bearing in mind however that in some cases it might be easier to influence one group rather than the other; and so even for dense networks, targeting non-users may still be the most effective approach.

6 Implementation

Assuming that the solution is to be implemented as either a 'dashboard' on a wall (perhaps by a thermostat) or as an app, we make some suggestions of different mechanisms that could be considered.

6.0.1 Gaming loop: Progress

User earns progress through:

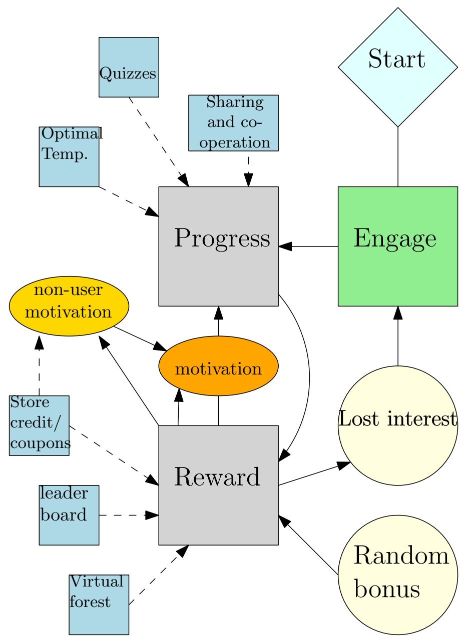

Figure 9: Schema of implementation

- staying within optimal temperate level, which can be visualised via a progress bar.
- completing quizzes (for dashboard users) over a longer timescale, dashboard users could complete postal questionnaires)
- giving feedback on comfort level - either in app or via a happy/sad button
- sharing and inviting other users

6.0.2 Gaming loop: reward

We distinguish between rewards that cater to an app-based implementation and dashboard-based.

For in-app rewards this could take the form of

- leader-board rankings enable people to compete with others in the building.
- virtual forest; as progress is earned, users collect virtual plants, similar to the approach of Farmville.
- progress is rewarded by unlocking games. In challenge mode, a user may earn 'store credit' for attaining certain scores, which can be used to buy things. The games do not

have to be complex, and could incorporate light educational content about the benefits of maintaining optimal heating temperature.

- users teaming up to earn greater rewards, following the Pokemon Go style.

For dashboard rewards

- visual progress bar including information about past behaviour and money saved, tapping into the approach used for example by fitbits
- being entered into prize draws, creating a lottery dynamic
- coupons that can be exchanged for items of small worth or discount with partner organisations.

We also propose targeting rewards at non-users. For example, store credit and coupons could be used to purchase toys that would appeal not directly to the user but to a child or grandchild. These would be low-cost items with a high appeal. In Section 5, we suggest how you might model this scenario.

6.1 Psychological framework of an engaging game

There are a few more things to consider when creating a game from psychological point of view. The more we know what things drive us to continue playing and make us hooked on the game the better we can build a game which is engaging. One such complete gamification framework is Octolysys created by Yu-kai Chou, which takes into account eight basic drives of human behaviour. Among those drives are Meaning & Calling, Empowerment & Creativity, Accomplishment & Development, Ownership & Possession, Social Influence & Relatedness, Scarcity & Impatience, Unpredictability & Curiosity, Avoidance & Loss. See an illustration in Figure 10 [1].

Yu-kai Chou divides those drives into two groups, on the one hand, by the logical and the emotional, he calls it Left Brain and Right Brain (strictly symbolical), and on the other hand, by negative and positive motivators, which he calls The Black Hat and The White Hat. In 10, Left Brain and Right Brain motivators are on the left and right sides of Octagon, respectively. Left Brain motivators are extrinsic, such as material rewards or anything that can be obtained, Right Brain Motivators are intrinsic, the activity itself is motivating enough. Techniques from the top half of the picture are called The White Hat Gamification and techniques from the bottom half are called The Black Hat Gamification. The White Hat is about positive motivation, about something that makes people feel good and powerful, express creativity, learn something, become better, smarter, more skilled. The Black Hat, on the contrary, is about negative motivation, about things that make people do something out of fear or out of desire to possess something, which can be considered manipulative. For more details and examples, see [14].

One more important thing to note is that too many external motivators can backfire and reduce motivation of a user, who already enjoys some activity, finds meaning and purpose in it [15]. The research has shown that too much of extrinsic motivation, for example money to perform some task, reduces the quality of performance, might diminish ethical reasons to do work properly [13] and, as mentioned above, also reduces a person's enjoyment.

This model can be used both for creating an engaging game and or for analyzing it when it is ready. Figure 11 provides a breakdown of the core drivers of gamification, which can be used for analysis of a given gamification system. In Figure 11, we apply this framework to the Fortum proposal. Basic principles are that an engaging game should have at least one drive and should be as balanced as possible in terms of extrinsic/intrinsic motivation and positive/negative motivation.

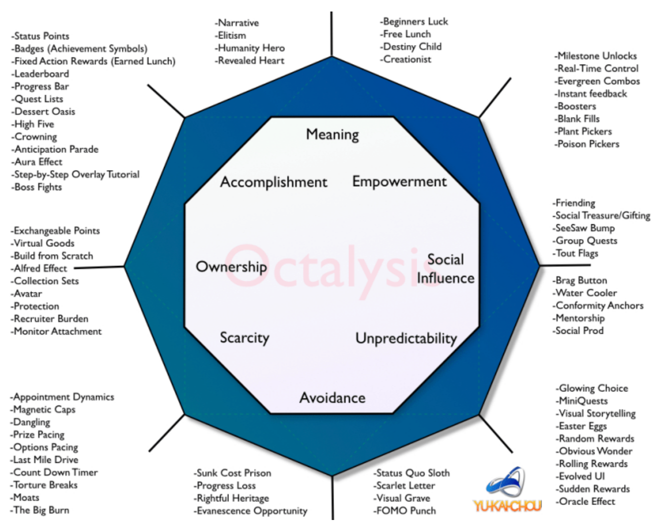

Figure 10: The Eight Core Drives of Gamification.

We suggest that to develop successful rewards, it would be of interest to consider the four-stage hook cycles[11], which explains how to form a habit for a consumer to buy some products. These stages are illustrated in Figure 12. Since external rewards can be tricky and backfire, we need to introduce as much internal reward into the game process as possible. According to the author of [11], there are three types of internal rewards, which are key in forming habits. Among them are "the reward of the tribe", which is about the sense of being a part of community, "the reward of the hunt", which is about satisfaction from reaching set goals or gaining progress, and "the reward of the self", which is about sense of meaning and self-development. These ideas have been demonstrated to be effective for promoting

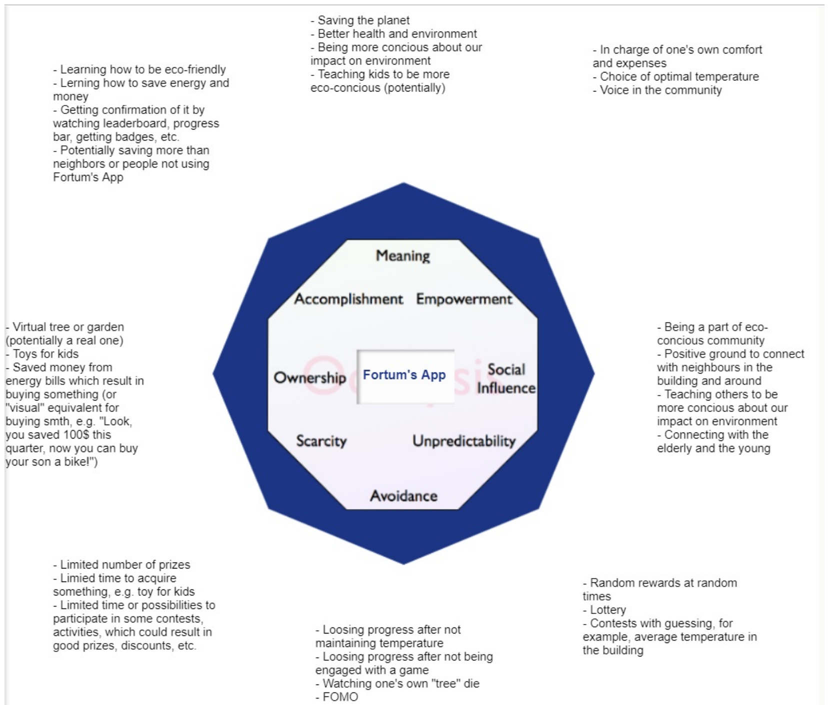

Figure 11: The Eight Core Drives for a prototype of Fortum's App.

eco-conscious behaviour; in[8], both Octalysis and The Hook Model are applied to analyze an eco-game called "Zero Waste Challenge".

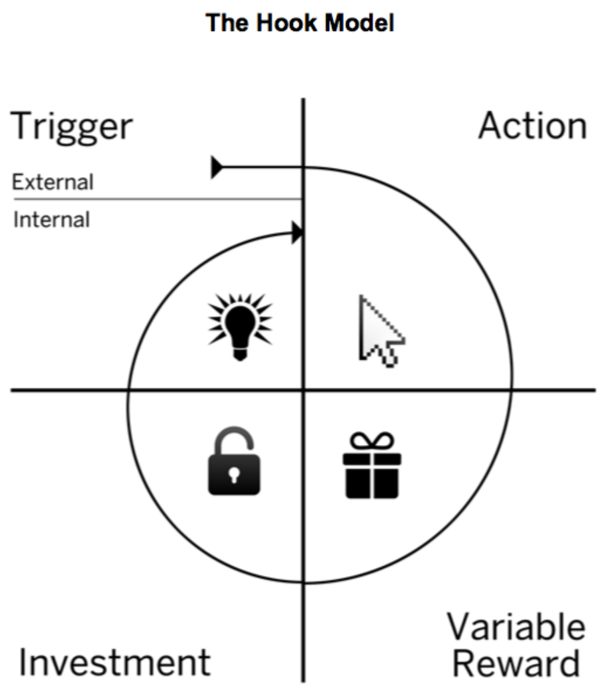

Figure 12: The Hook Model.

Finally, we also would like to outline some observations from demographic studies regarding Poland and Poles, which may become useful while designing and promoting a game:

- Life expectancy of women in Poland is greater than that of men. [2]
- Growth of female population is larger than growth of male population.[2]
- Women are more likely to play number games, men are more willing to engage in bets and gambling machines. [4]
- Potential improvement in assets is a key factor in gambling among seniors. [4]
- The main declared goal of winning money is to improve the quality of life of children (grandchildren) through financial support. [5]
- Lotteries in the form of scratchcards, and numerical games are seen as entertainment, unlike card games or roulette. [3]
- The number of religious people is much larger among older people than younger or middle-aged people. In particular, a larger proportion identify as belonging to a parish. [6]

7 Discussion and recommendations

We have presented a model for a gamification of heating temperature usage, suggested some specific game mechanisms, and highlighted mathematical frameworks for the following:

1. Determining reward given a user's progress.
2. Weighting reward relative to time for different tasks, as a method for encouraging engagement at an early stage.
3. The interplay between user characteristics and reward types.
4. The interaction between users and external influencers.

Whilst these are only outlines of the approach, we hope they will be useful in the prototype stage.

We would particularly like to highlight the following recommendations:

- Reward should cater to different demographics and most likely a combination of different rewards will be required.
- Hard to motivate groups may be reached through users outside the game, e.g. through targeting children and grandchildren.
- Rewarding easier tasks at an early stage is one method for promoting early adoption.

Overall, the principles of gamification have huge potential to achieve Fortum's aim of engaging users in the temperature control of their building. However it is important to fully understand the interplay between reward systems and progress in order to effectively implement such a solution.

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