

BACKGROUND

- Municipalities need to raise awareness among food-related businesses (FRBs) that face regulations and accommodate source-level food waste (FW) management using composters/digesters (C/Ds) to reduce greenhouse gas emissions.
- IoT-based gamification can invite user engagement in smart city applications. At the same time, performing user behavior analysis with machine learning (ML) reduces complexity and time of gamification adjustments, ensuring its continued relevance and effectiveness, and driving sustained engagement in the long run.
- Generic application gamification approach can address policy complexity and diverse user behaviors, though expert input is still needed.

PROPOSED SOLUTION

- An AI-assisted gamification platform for smart city FW management to reward FRB and their employees for adopting a FW digester at the source.
- Combination of a **single rewarded task approach** and a **user classification ML model for automatically adjusting gamification rules**.
- Aims to support wider adoption by making it accessible to non-expert users, while **prioritizing transparency and user control**.

1. GAMIFICATION CONTEXT AND APPROACH

Any system that can distinguish and log a **drop in a C/D**, tied to an **individual account**, with its **volume measured by weight**, can potentially be integrated into the same gamification framework, to **deliver personalized rewards based on the drop action**.

Table 1: Context defined as a generic single-task requiring singular entities

FOOD WASTE CONTEXT LEVEL SCHEME			
Single action	One measurable object	in relation to	an IoT system
Drop	urban FW (per kilogram)	inside	a FW container

Member and team rewards are calculated based on the applied rules configured by the gamification strategy administrator (GSA).

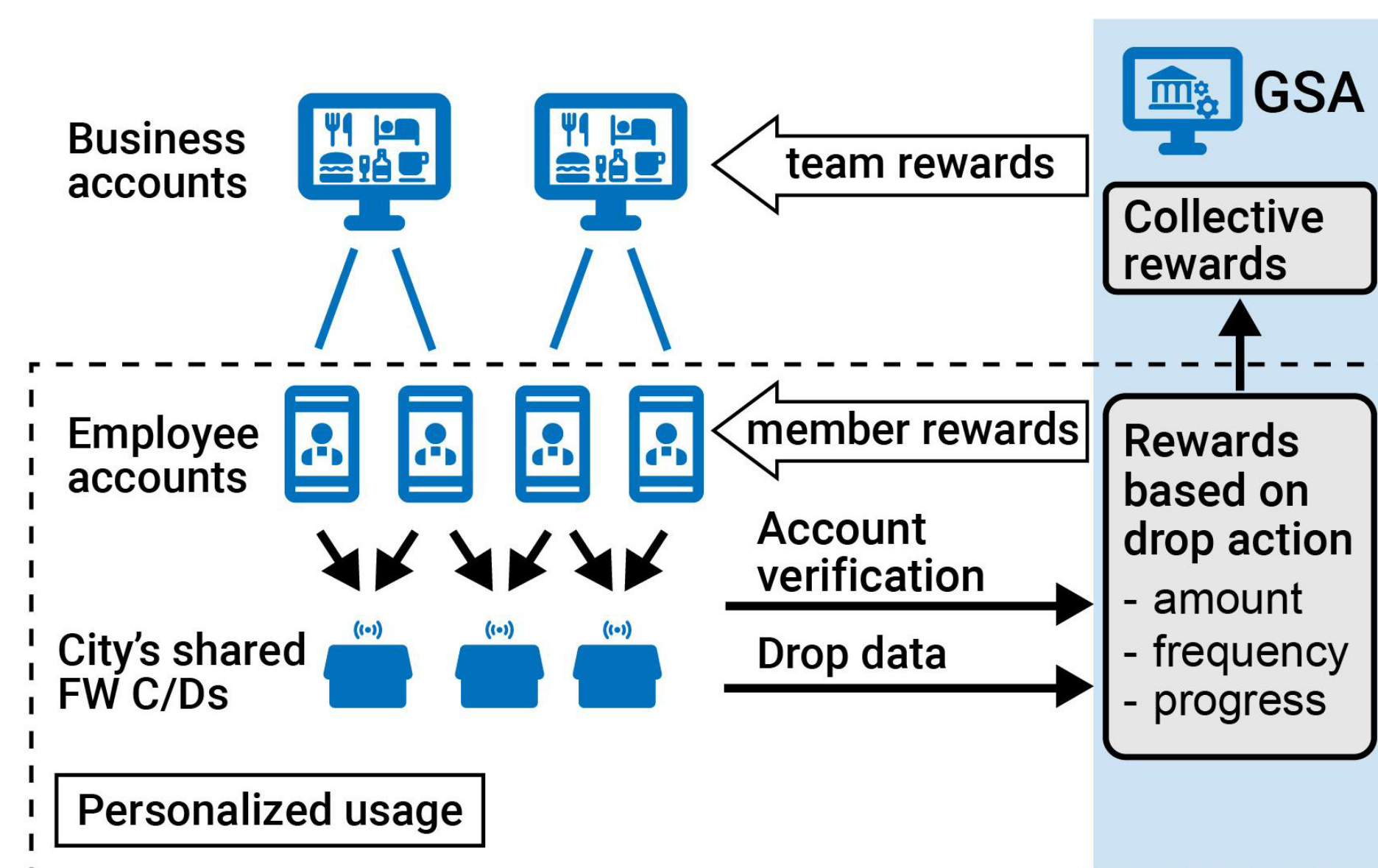


Figure 1: Conceptual diagram of the FW gamification platform

2. ML MODEL

Eight ML models were evaluated to predict users' willingness to use a FW digester. Users were classified as "**willing**" or "**unwilling**" to use it. Recency, Frequency, and Monetary (RFM) analysis was used for feature extraction, which measured time since the last transaction (drop), drop frequency, and total waste deposited by each user. **CNN outperformed** the other models, achieving higher F1-score.

Table 2: Classifiers simulation results

Classifier	Accuracy	Recall	Precision	F1-Score
XGB	87.80%	90.47%	77.55%	83.51%
LR	88.61%	85.71%	81.81%	83.72%
GNB	82.11%	92.85%	67.24%	78.00%
RF	90.24%	95.23%	80.00%	86.95%
SVC	89.43%	88.09%	82.22%	85.05%
DT	81.30%	76.19%	71.11%	73.56%
k-NN	87.80%	95.23%	75.47%	84.21%
CNN	91.05%	96.67%	80.15%	87.64%

3. AI-TAILORED RULES

Valuing **positive feedback**, the adjustment is applied to "unwilling" accounts by **increasing the reward** for the same effort (tailored rule action), or by **decreasing the effort** for the same reward (tailored rule condition).

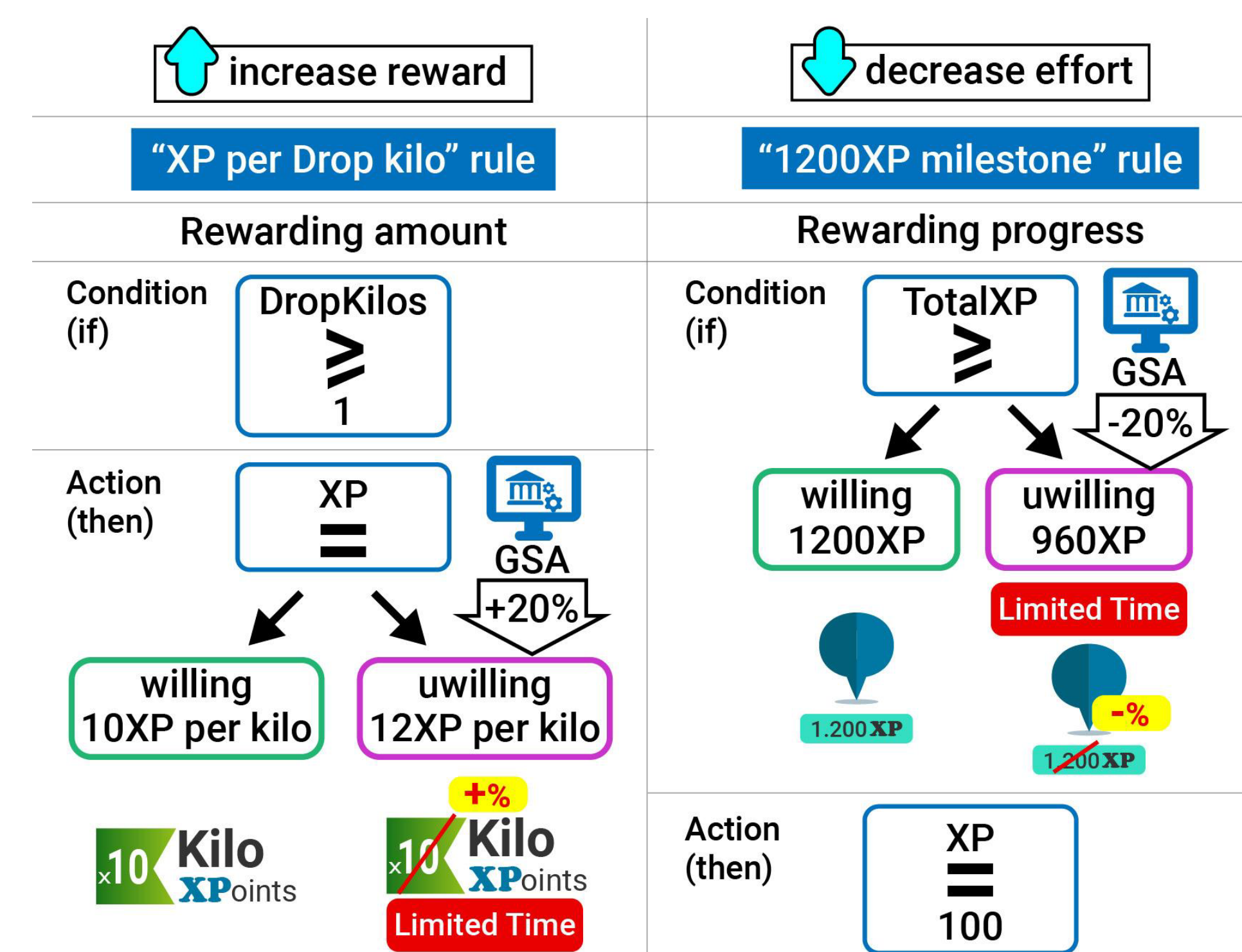


Figure 2: Adjust reward (left) and condition (right)

The GSA has control over the rule adjustment by configuring percentage of increase or decrease in relation to the default values of the rule.

Figure 3: Adjust reward (left) and condition (right)

CONTRIBUTIONS

- Utilizing RFM analysis for CNN user classification is the appropriate method to classify FW processor users, based on drop data.
- Single-task based gamification strategy can be combined with ML user behavior analysis. As a sufficiently generic approach, it can be adaptable for policymakers and practical for wide adoption, while prioritizing transparency and user control by non-expert users.