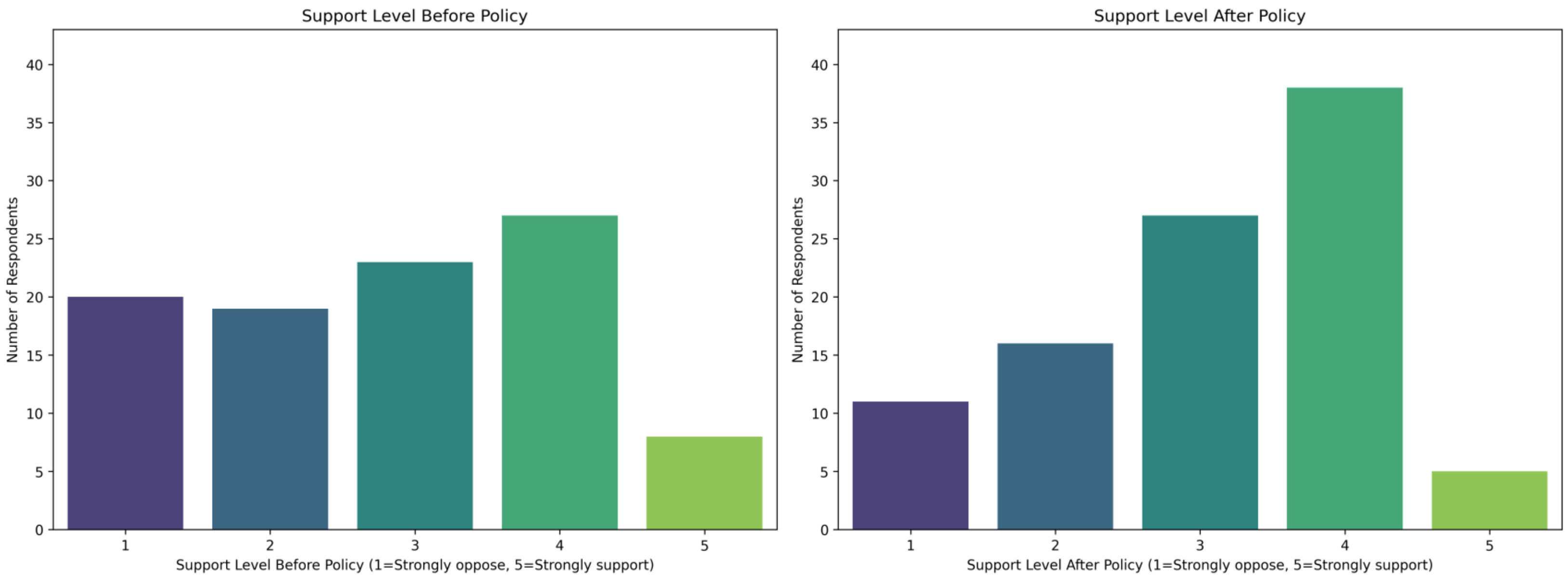
Case Study I: Public Willingness Toward the Municipal Solid Waste (MSW) Charging Policy

GCAP3226 2025/09/16

Recap of week 2

Public willingness to support MSW charging policy is assessed by data visualization.



72% against policy (Sing Tao News Corporation; Source URL : Survey: 72pc against reviving waste-charging, fear costs amid better recycling habits | The Standardhttps://www.thestandard.com.hk/hong-kong-news/article/311098/

Objectives of Case Study I

- To equip students with **analytical tools** for data-informed policymaking in Hong Kong (CILO 1)
- To explore using **linear regression models** to analyse public willingness
- Policy recommendation

Structure of Case Study I

- Background
- Study design
- Linear Regression models
- Results Interpretation
- Recommendations

- In-class Exercise

Background

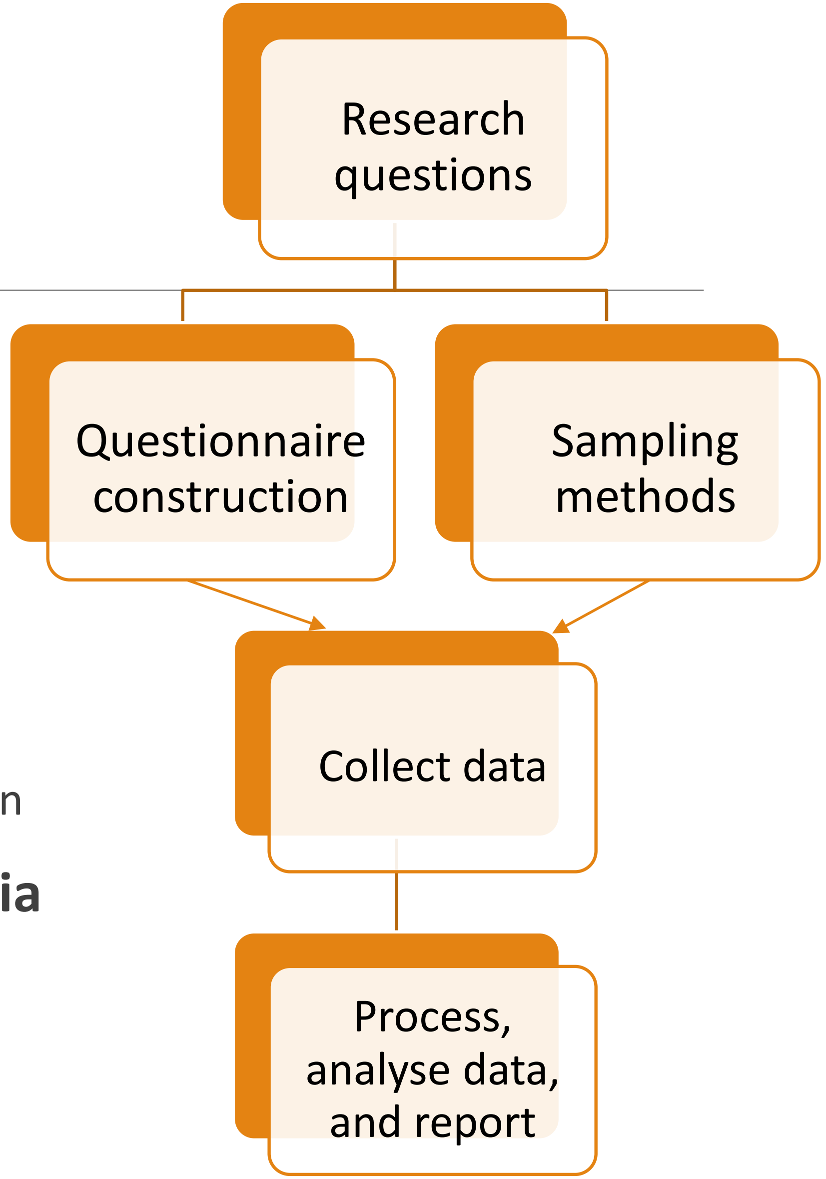
- Hong Kong's waste amount: 3.97 million tonnes of MSW in 2023 (EPD, 2023)
- 2 landfills projected to be exhausted in 2026 (Government Press Releases, 2024)

Policy Background

- “Polluter Pays” Principle: requires waste producers to bear the cost of disposal based on the quantity generated, incentivizing waste reduction and recycling.

- Applies to all sectors producing MSW, including residential (domestic) and non-residential (commercial and industrial) premises.

Study design



Questionnaire construction

- Specify response variable (y) and exploratory variables (x)

Sampling methods

- Probability sampling: **randomly** selecting samples
  - Representative sample; results can be generalized to the entire population
- Nonprobability sampling: samples are selected based on **criteria other than random chance ->** exploratory analyses
  - Convenience sampling: chosen based on relative ease of access
  - Snowball sampling: respondents refer acquaintance

Statistical Background: Regression Models

- **Linear Regression**: model **continuous** response variable (e.g., amount willing to pay) vs explanatory variables
  - Assumes a **linear** relationship $y = \beta_0 + \beta_1 x + \epsilon$
  - Estimates the **effect** based on observed data
  - Quantifies the **expected change** in response for a **one-unit increase** in an explanatory variable, holding other variables the same

- **Logistic Regression**: model **binary** response variable (e.g., support vs. oppose)
- **Ordinal Regression**: model **ordinal categorical** response variable (e.g., oppose, neutral, support)

Not Causal Inference!

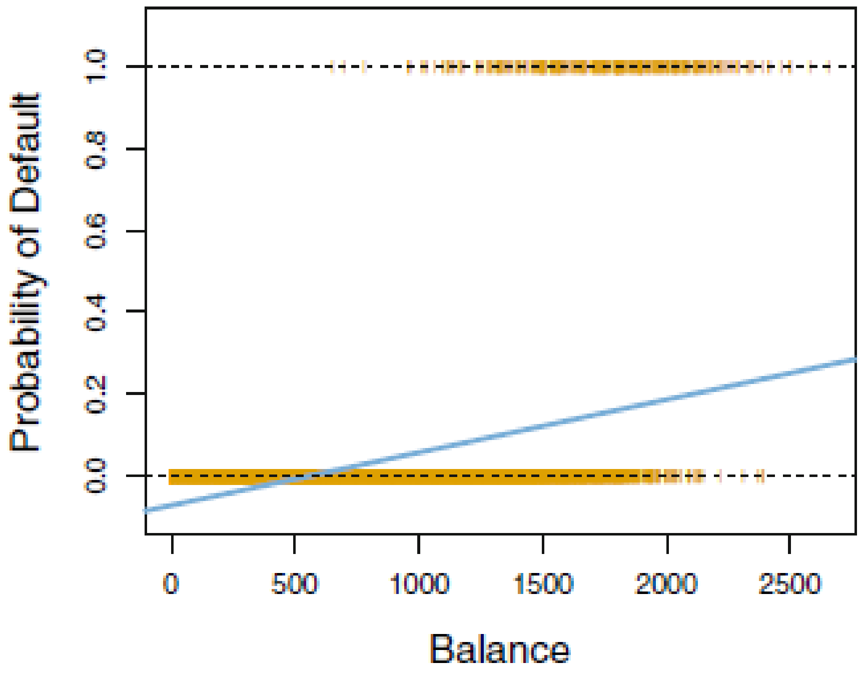
Model binary response

- To model the **probability** that Y belongs to a particular category, rather than modelling the response as 0 or 1 directly.

$P(Y = 1) = \beta_0 + \beta_1 X?$

- However, unreasonable prediction may occur.

- Transform $P(Y = 1)$ using a function that gives outputs between 0 and 1 for all values of X.



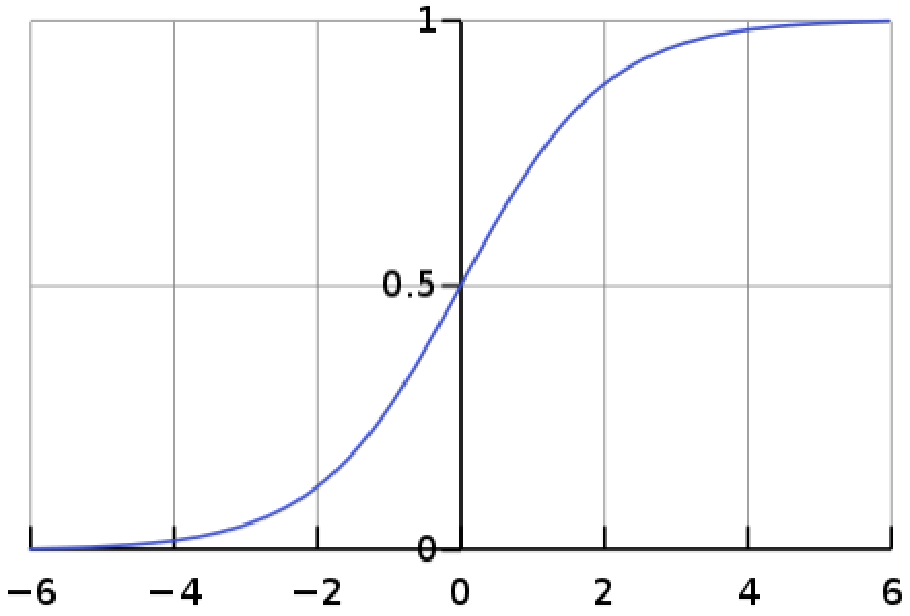
Logistic regression model

- Many functions meet this criterion, logistic regression uses the **logistic function**
- The standard logistic function is

$$f(x) = \frac{1}{1 + e^{-x}}$$

- Accordingly,

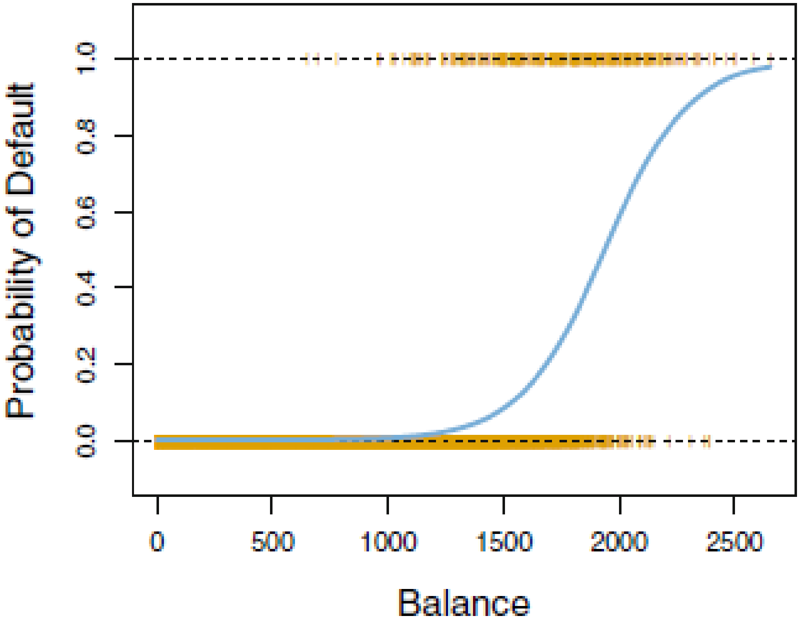
$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X)}}$$

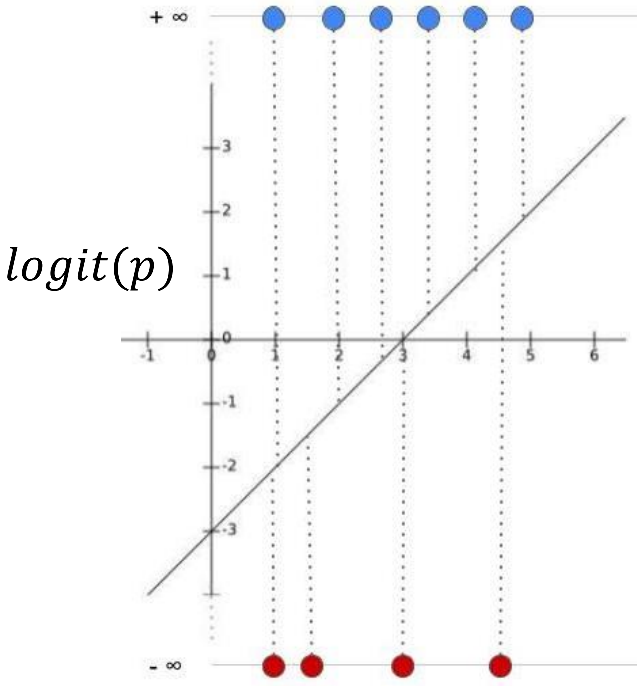


Logistic regression model

$$P(Y=1) = p = \frac{1}{1+e^{-(\beta_0+\beta_1 X)}}$$

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X$$





Interpretation of model coefficients

- $\frac{p}{1-p}$ is called odds.
- E.g., p is the probability of winning a game. If $p = ½$, the odds of winning is 1:1.
- $\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X$
- β_0 is the log odds of y = 1 when x = 0
- β_1 is the **change of log odds** of y = 1 with 1 unit change of x. If x is binary, β_1 is the **log odds ratio** of y = 1 of the x = 1 group vs the x = 0 group.
- Odds ratio = 1 (>1,<1) means exposure does not affect (associated with higher, lower) odds of y = 1

Ordinal logistic regression model

$P(Y \leq 1) = \pi_1, P(Y \leq 2) = \pi_1 + \pi_2,\ \pi_1 + \pi_2 + \pi_3 = 1$

$$logit\big(P(Y \leq 1)\big) = ln\left(\frac{\pi_1}{\pi_2 + \pi_3}\right) = \alpha_1 - \beta x$$

$$logit\big(P(Y \leq 2)\big) = ln\left(\frac{\pi_1 + \pi_2}{\pi_3}\right) = \alpha_2 - \beta x$$

Brief summary of regression results

- Regression models on public support for Hong Kong's waste charging policy, based on 97 non-probability samples.
- Key predictors: Perceived government responsiveness (coefficient ≈ 0.54, $p<0.01$; increases odds of higher willingness).Perceived policy fairness (coefficient ≈0.42, $p<0.01$).Model fit: $R^2 \approx 0.61$ (adequate but exploratory).
- Limitations: Small, non-representative sample risks selection bias (e.g., educated over-representation), limiting generalizability; needs validation via larger probability-based surveys (e.g., n=500+ stratified random samples).

Policy recommendation

- Prioritize responsiveness: Enhance public engagement (e.g., town halls, online portals) to build trust, potentially boosting willingness by 0.5 points improvement, pending validation in larger, probability-based samples.
- Address fairness secondarily: Implement transparent equity (e.g., low-income subsidies).
- Preliminary evidence from the pre-post analysis suggests that targeted information on Hong Kong's waste crisis severity and policy benefits may enhance public support for MSW charging.