Final Individual Assingment

Provide a very brief executive summary that includes a description of the problem you have studied as a group, an explanation and justification of the methodology you used, and a summary of your main takeaways.

To optimise Santander Cycles' revenue, we designed a pricing model that incorporates peak and off-peak fares based on consumers' willingness-to-pay (WTP). This approach significantly increases projected daily revenue. For demand redistribution between high- and low-demand stations, we encountered challenges with the two-fare classes principle due to varying station capacities. Instead, we adopted a snapshot-based approach that dynamically models prices to reflect real-time station availability. By integrating this into the Santander app, users can maximise their surplus in real time. Additionally, investing in a machine learning algorithm to account for various external events, such as tube strikes—which increase bicycle demand by 85% (Saberi et al., 2018)—can significantly improve the quality of data used to predict pricing strategies.

Provide one direction in which you think the project can be extended. Please describe clearly how you would work on that extension. For example, what methodologies would you apply and how, what type of data would you need, etc. You are not asked to formally work on this extension or provide any results.

To extend this project, we propose refining pricing strategies through user segmentation. Categorising users into commuters and tourists, each with distinct price elasticities and behavioural patterns, allows pricing to better meet their needs. This segmentation requires collecting user-specific data, including rental patterns, trip durations, and station usage. For example, commuters are identifiable through frequent, short rides during peak hours, while tourists can be characterised by longer, irregular trips and activity near popular landmarks. Analysing this data enables more accurate demand predictions and better classification of users.

This segmentation can be incorporated into a Multinomial Logit (MNL) model to estimate segment-specific demand elasticities. The MNL model predicts the probability of a user selecting a particular service option (e.g., price or station) based on variables such as price, travel time, and convenience. Segment-specific utility functions capture user preferences, with commuters prioritising availability and convenience during peak hours, while tourists place greater emphasis on price and accessibility.

$$U_{ij} = \beta_1(\text{Price}) + \beta_2(\text{Travel Time}) + \beta_3(\text{Convenience}) + \epsilon_{ij} \tag{1}$$

Dynamic pricing strategies, informed by elasticity estimates, would prioritise higher prices during peak hours for commuters and targeted discounts for tourists at low-demand stations. For commuters, higher prices during peak hours would help prioritise bike availability, while discounts during off-peak hours could encourage demand shifts. For tourists, targeted discounts at low-demand stations or during off-peak times would stimulate rentals while maintaining affordability. Enhancing the current machine learning framework allows for real-time price adjustments based on updated demand forecasts, external factors like tube strikes, and evolving user behaviour.

This approach delivers tangible benefits. Revenue optimisation captures commuters' willingness-to-pay during peak hours while stimulating tourist demand in underutilised areas. Improved demand redistribution enhances operational efficiency, minimises station imbalances, and reduces costly redistribution efforts. Tailoring pricing strategies to user segments increases customer satisfaction, fostering loyalty and repeat usage (Melnic, 2016). This is crucial for the long-term viability of Santander Cycles, as demand for bikes has reached its lowest point in a decade, as shown in Table 1. Integrating user segmentation into its pricing strategy enables Santander Cycles to increase revenue, improve resource utilisation, and deliver a user-centric service—marking a significant departure from its flat-fee model.

Please briefly comment on which topics you found most interesting in this module and which topics you would like to learn more about.

I have always been fascinated by the intersection of psychology and business, particularly how strategies influence consumer behaviour. Assortment optimisation was the most interesting topic for me, as it highlights how data-driven approaches shape decision-making and differentiate product offerings. The integration of data collection to refine these strategies was especially compelling, introducing concepts I had not previously considered. Moving forward, I aim to deepen my understanding of pricing strategies with consumer choice models, specifically exploring how machine learning can improve precision and applicability in dynamic markets.

Appendix

Year	Number of Bicycle Hires
2014	10,023,897
2015	9,871,839
2016	10,303,637
2017	10,446,044
2018	10,567,540
2019	10,168,936
2020	10,434,167
2021	10,941,264
2022	11,505,872
2023	8,531,168
2024	7,530,359

Table 1: Number of Bicycle Hires (2014-24)

Data is based on raw data from the Greater London Authority.

Reference

Greater London Authority, 2024, *Number of Bicycle Hires*, Greater London Authority, accessed 12 December 2024, https://data.london.gov.uk/dataset/number-bicycle-hires.

Melnic, E.L., 2016. How to strengthen customer loyalty, using customer segmentation?. *Bulletin of the Transilvania University of Brasov. Series V: Economic Sciences*, pp.51-60

Saberi, M., Ghamami, M., Gu, Y., Shojaei, M.H.S. and Fishman, E., 2018. Understanding the impacts of a public transit disruption on bicycle sharing mobility patterns: A case of Tube strike in London. *Journal of Transport Geography*, *66*, pp.154-166.