Crowdsourcing for Omnichannel Fulfillment: Integrating Task Assignment and Discrete Choice Models of Customer Participation

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Problem Definition

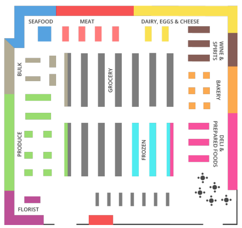
Leveraging in-store customers in online order picking operations

In-store Picking → Order Delivery

In-Store Customers
- Shopping List
- Arrival Time
- Segment

Online Orders
- Arrival Time
- Requested Items
- Deadline

Physical Store



Layout

Online Store

Motivation

- Need for balance the trade-offs between physical and online presence on omnichannel stores
- Over-looked aspects of order collecting – order picking *(~55% of the overall order collecting cost)*
- Offering intregrated and value-added services through novel business models for customer engagement
- Scalable solution in volatile grocery demands

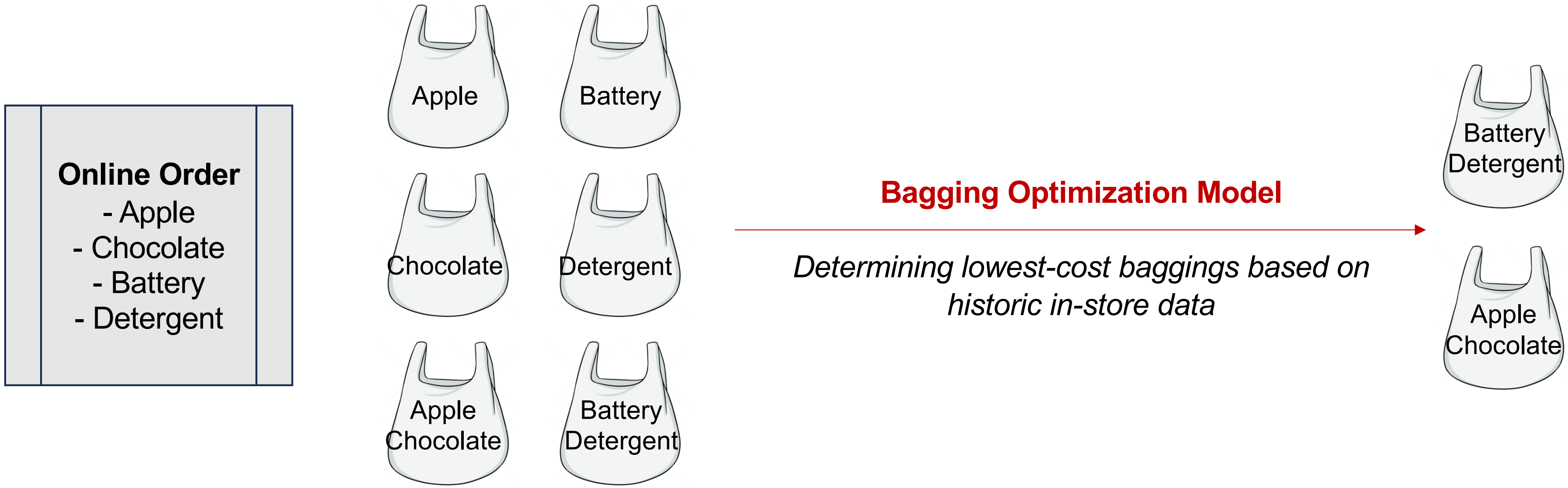
1. REAL-TIME TASK ASSIGNMENT

Solution Approach

Bagging → Data Farming → Machine Learning Algorithms → Real-Time Assignment Strategies → Evaluation of the Model Results

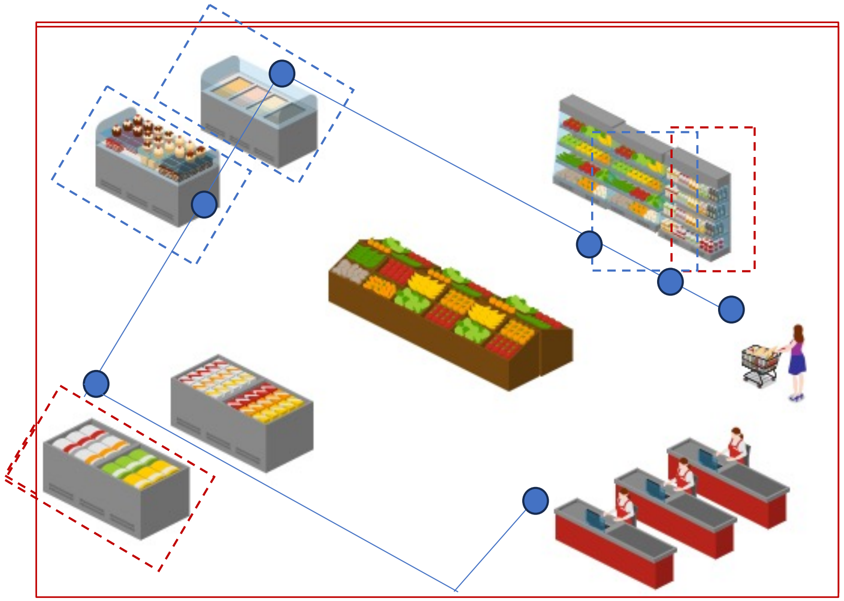
Solution Approach (I/V)

Bagging → Data Farming → Machine Learning Algorithms → Real-Time Assignment Strategies → Evaluation of Model Results



Solution Approach (II/V)

Bagging | **Data Farming** | Machine Learning Algorithms | Real-Time Assignment Strategies | Evaluation of Model Results

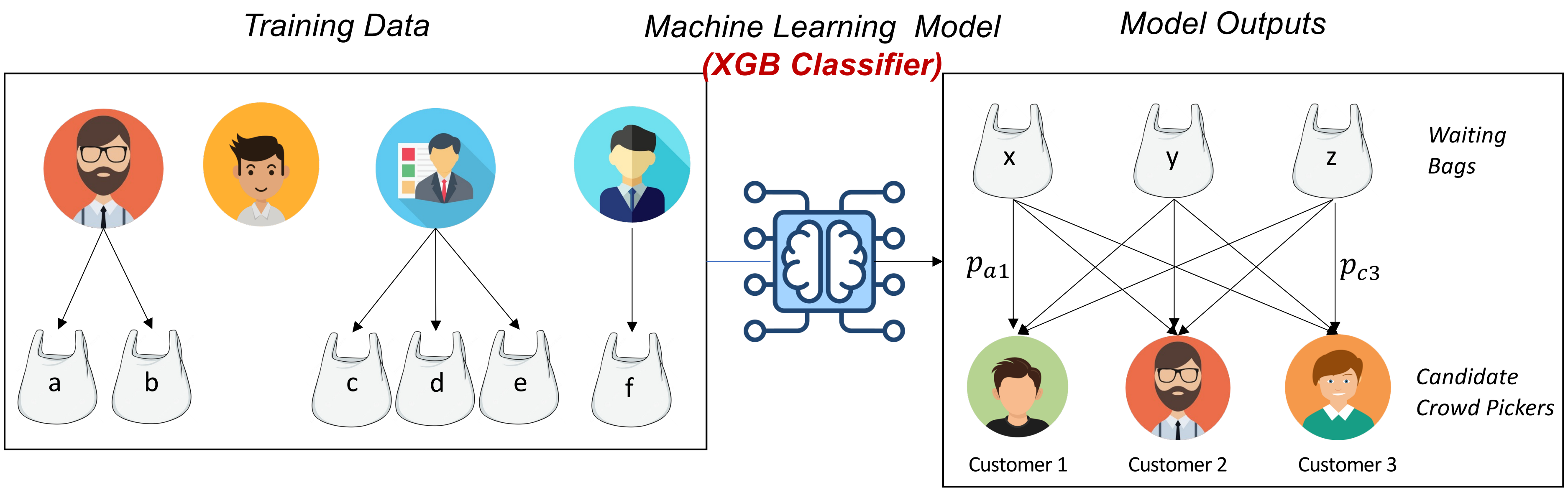


- Generalized Assignment Problem (GAP)
  - Customer specific costs
  - Customer-order pair
  - Maximum picking time, weight and volume

- Customer participation rates (expected cost minimization)
- Clairvoyant Decision-Making

Solution Approach (III/V)

Bagging → Data Farming → **Machine Learning Algorithms** → Real-Time Assignment Strategies → Evaluation of Model Results



Solution Approach (IV/V)

Bagging → Data Farming → Machine Learning Algorithms → **Real-Time Assignment Strategies** → Evaluation of Model Results

Random Score

Benchmark 1.1:

- Assignment score → Daily determined by rolling a dice *(constant)*

Benchmark 1.2:

- Assignment score → Continuously determined by rolling a dice for customer and bag pair (continuous)

Direct Assignment

Benchmark 2.1:

- Direct assignment based on lowest-cost customer-bag pair

Benchmark 2.2:

- Direct assignment of the bag with earliest deadline

Machine Learning Score

Benchmark 3.1:

- Assignment score → Machine learning score

Benchmark 3.2:

- Assignment score → Machine learning score + prioritization based on deadline

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Solution Approach (IV/V) – *Illustrative Example*

Bagging → Data Farming → Machine Learning Algorithms → **Real-Time Assignment Strategies** → Evaluation of Model Results

Threshold = 0.8

Machine Learning Score

Bag Number	Assignment Score	Time-Load	Maximum Time-Load	Time to Delivery	Assignment
1	0.64	7	18	10	0
2	0.73	8	18	13	0
3	0.82	6	18	7	0
4	0.87	5	18	8	1
5	0.93	10	18	11	1

Machine Learning Score + Prioritized Deadline

Bag Number	Assignment Score	Time-Load	Maximum Time-Load	Time to Delivery	Assignment
1	0.64	7	18	10	0
2	0.73	8	18	13	0
3	0.82	6	18	7	1
4	0.87	5	18	8	1
5	0.93	10	18	11	0

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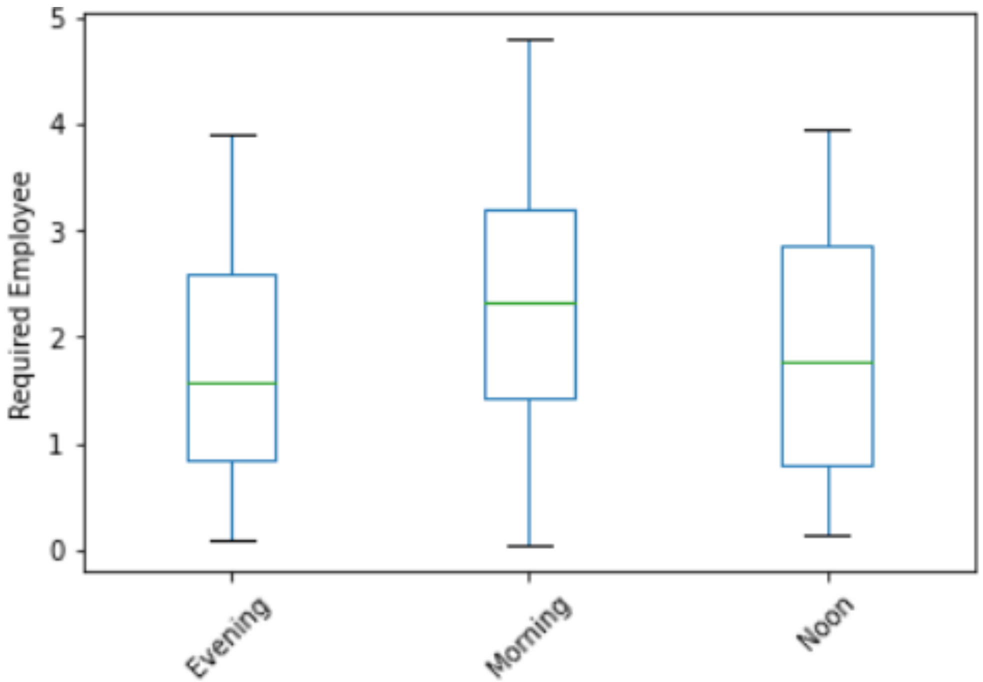
Solution Approach (V/V)

Bagging → Data Farming → Machine Learning Algorithms → Real-Time Assignment Strategies → **Evaluation of Model Results**

Benchmark	Existing Model	Under-Sampling	Over-Sampling
B 1.1 (Constant random Threshold)	58,89%	43,35%	39,87%
B 1.2 (Continuous random Threshold)	58,01%	70,26%	39,34%
B 2.1 (Cost based direct assignment)	75,37%		
B 2.2 (Delivery time based direct assignment)	55,59%		
B 3.1 (Machine Learning)	40,76%	18,46%	17,46%
B 3.2 (Delivery time based machine learning)	34,45%	9,45%	**8,60%**

Managerial Insights - *Required Number of Dedicated Pickers*

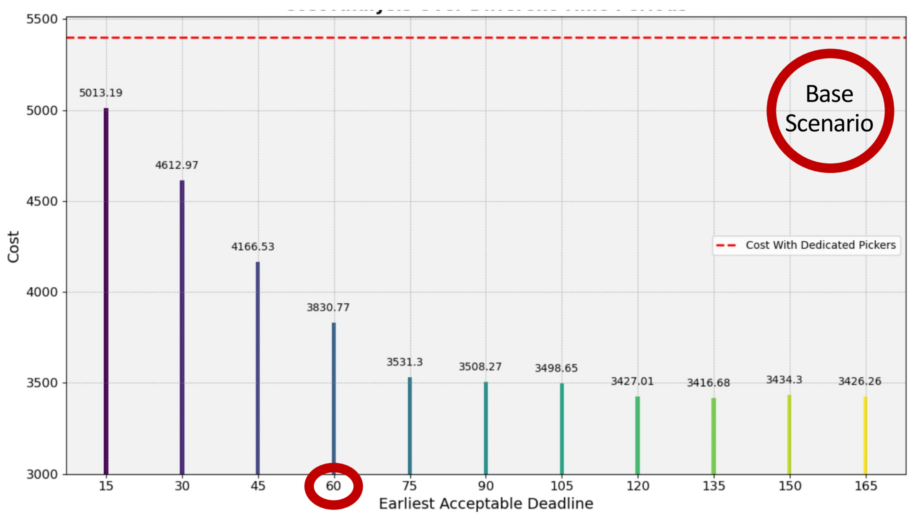


Required number of dedicated pickers varies **from 0 to 5**

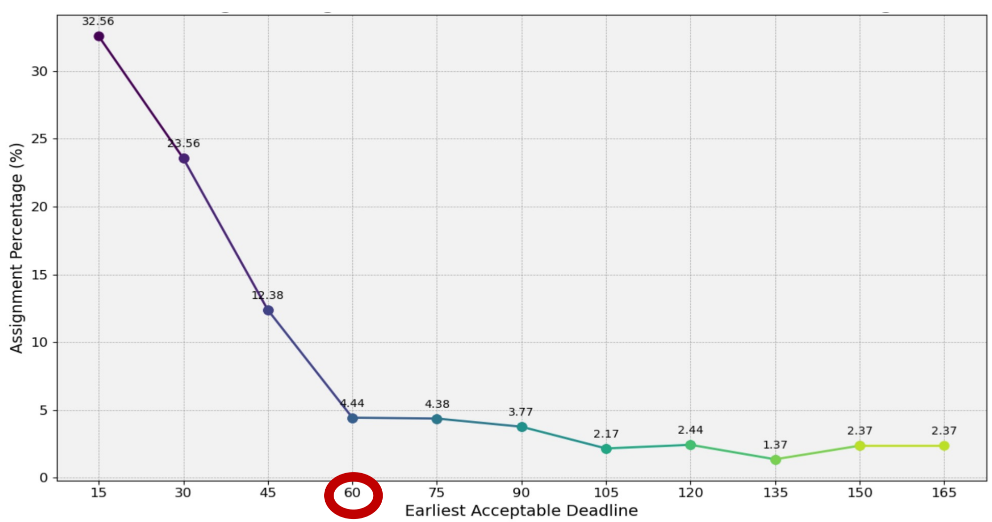
Order volumes change significantly in **different periods within a day**

Managerial Insights – *Service Level Sensitivity*

Total Cost based on Acceptable Earliest Deadline



Assignment Percentages based on Acceptable Earliest Deadline



2. DISCRETE CHOICE MODELS OF CUSTOMER PARTICIPATION

Experiment Design

1
Phase – 1
Problem & Decision Context

Experiment
Picking tasks to in-store customers

Decision maker
Physical in-store shoppers

Alternatives
- Package 1
- Package 2
- Opt-Out

2
Phase – 2
Attribute & Level Definition

Item count: {3, 6, 9…}

Aisle Count: {1, 3, 5}

Reward type: {charity, priority…}

Reward amount: {low, high..}

Item Familiarity: {Yes, No}

Heavy Item: {Yes, No}

3
Phase – 3
Design

Full factorial design:
+550 scenario

D-efficient design:
160 scenario
MNL D-error: 0.075

17Scenario 1

	task1	task2
itemnumber	6	2
aislenumber	1	1
physicaleffort	2	1
itemfamiliarity	1	1
storefamiliarity	1	1
shoppingmission	2	1
compensationtype	1	3
compensationamount	100	10
Choice question:		

4
Phase – 4
Blocking

8 choice task per respondent

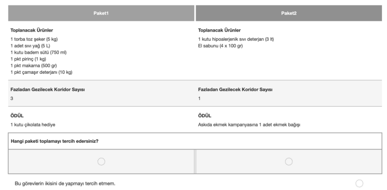
20 block

Objective:
•Reduce cognitive burden
•Improve response quality

5
Phase – 5
Survey

+750 respondents

160 scenario



Stated Preferences Survey

- **750+** Participants

500 from control group
250 from focus grocery

- **6000+** Design rows

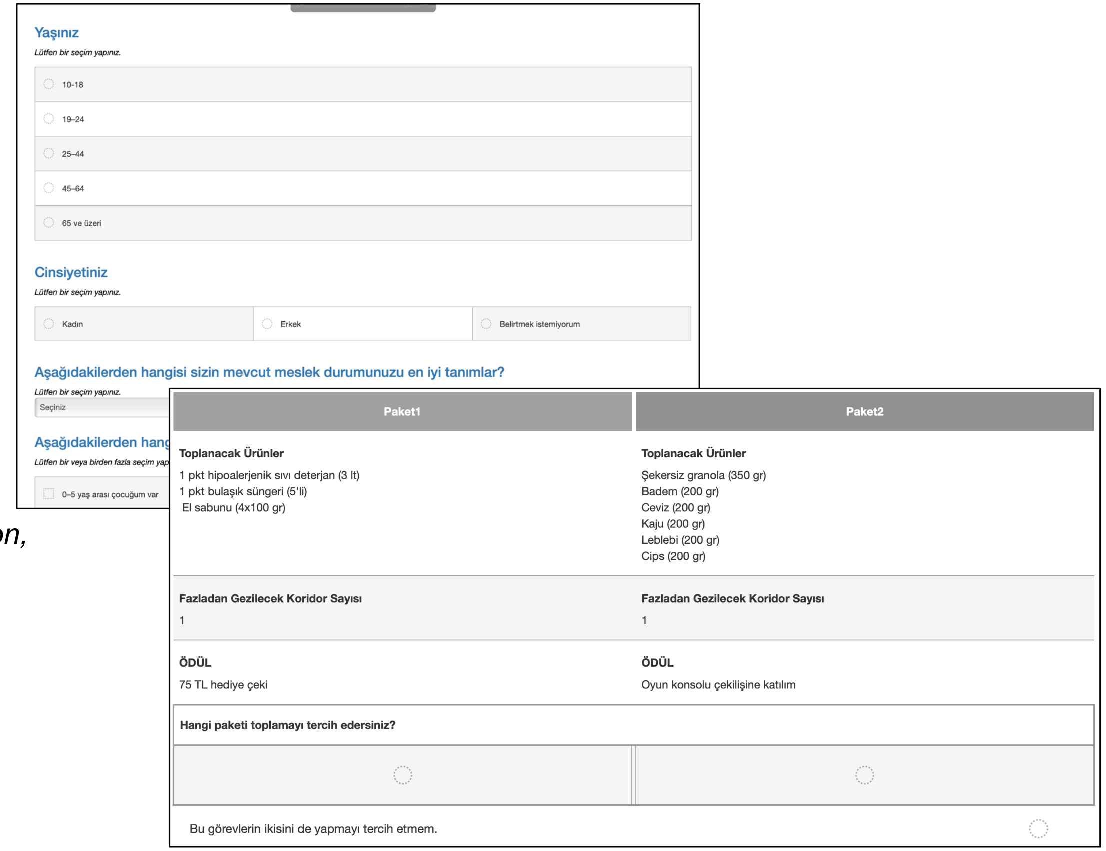
8 questions per participant

- **11+** Characteristics

Age, gender, shopping day/time, shopping frequency, occupation, average income, frequently visited aisles, children status

- **4** Different compensation types

Checkout priority, charity, monetary, lottery, product



Yaşınız
Lütfen bir seçim yapınız.
10-18
19-24
25-44
45-64
65 ve üzeri

Cinsiyetiniz
Lütfen bir seçim yapınız.
Kadın
Erkek
Belirtmek istemiyorum

Aşağıdakilerden hangisi sizin mevcut meslek durumunuzu en iyi tanımlar?
Lütfen bir seçim yapınız.
Seçiniz

Aşağıdakilerden hang
Lütfen bir veya birden fazla seçim yap
0-5 yaş arası çocuğum var

Paket1	Paket2
Toplanacak Ürünler 1 pkt hipoalerjenik sıvı deterjan (3 lt) 1 pkt bulaşık süngeri (5'li) El sabunu (4x100 gr)	**Toplanacak Ürünler** Şekersiz granola (350 gr) Badem (200 gr) Ceviz (200 gr) Kaju (200 gr) Leblebi (200 gr) Cips (200 gr)
Fazladan Gezilecek Koridor Sayısı 1	**Fazladan Gezilecek Koridor Sayısı** 1
ÖDÜL 75 TL hediye çeki	**ÖDÜL** Oyun konsolu çekilişine katılım

Hangi paketi toplamayı tercih edersiniz?

Bu görevlerin ikisini de yapmayı tercih etmem.

Utility Specification

For each customer c and bag alternative b → total utility has two components:

$$U_{cb} = U_{cb}^{\text{bag}} + U_{cb}^{\text{comp}}$$

1. Bag-related utility

- **FAM_b**: familiarity with the bag
- **HB_b**: heavy / bulky indicator
- **$PTIME_b$**: picking time
- **$TTIME_{cb}$**: additional travel time

2. Compensation-related utility

- **$MONEY_{cb}$**: monetary compensation offered for bag b to customer c
- **$CHARITY_{cb}$**: donation amount allocated to a charitable cause
- **$PRODUCT_{cb}$**: reward in the form of a free product
- **$LOTTERY_{cb}$**: lottery-based incentive
- **$PRIORITY_{cb}$**: priority benefit (e.g., faster checkout)

Utility Specification – Customer Characteristics

Demographics:
- Y_c young
- O_c: old
- F_c: female

Shopping context:
- W_c: weekend shopping
- S_c: short trip

Household & employment:
- C_c: small child in household
- H_c: homemaker
- ST_c: student
- R_c: retired
- E_c: self-employed

Interaction Terms:

- Homemaker × Weekend
- Homemaker × Short Trip
- Small Child × Short Trip
- Young × Self-Employed
- Retired × Weekday
- Student × Short Trip
- ….
- ….
- ….

- Y_C= 1if customer c is young, 0 otherwise
- O_C= 1 if customer c is old, 0 otherwise
- H_C= 1 if customer c is a homemaker, 0 otherwise
- W_C= 1 if the shopping trip occurs on a weekend, 0 otherwise
- E_C= 1 if customer c is self-employed, 0 otherwise
- ……….
- ……….

Utility Specification – Final Utility Function

$$U_{cb} = U_{cb}^{\text{bag}} + U_{cb}^{\text{comp}}$$

$$U_{cb}^{\text{bag}} = \beta_{\text{FAM}}(c)\,\text{FAM}_b + \beta_{\text{HB}}(c)\,\text{HB}_b + \beta_{\text{PTIME}}(c)\,\text{PTIME}_b + \beta_{\text{TTIME}}(c)\,\text{TTIME}_{cb}$$

$$\beta_{\text{FAM}}(c) = B_{\text{FAM}} + b_{\text{FAM,young}}Y_c + b_{\text{FAM,old}}O_c + b_{\text{FAM,female}}F_c + b_{\text{FAM,weekend}}W_c + \cdots + b_{\text{FAM,HW}}(H_cW_c) + b_{\text{FAM,YE}}(Y_cE_c) + \cdots$$

$$\beta_{\text{HB}}(c) = B_{\text{HB}} + b_{\text{HB,young}}Y_c + b_{\text{HB,old}}O_c + b_{\text{HB,weekend}}W_c + \cdots + b_{\text{HB,HW}}(H_cW_c) + b_{\text{HB,YE}}(Y_cE_c) + \cdots$$

$$\beta_{\text{PTIME}}(c) = B_{\text{PTIME}} + b_{\text{PTIME,young}}Y_c + b_{\text{PTIME,old}}O_c + b_{\text{PTIME,weekend}}W_c + \cdots + b_{\text{PTIME,HW}}(H_cW_c) + b_{\text{PTIME,YE}}(Y_cE_c) + \cdots$$

$$\beta_{\text{TTIME}}(c) = B_{\text{TTIME}} + b_{\text{TTIME,young}}Y_c + b_{\text{TTIME,old}}O_c + b_{\text{TTIME,weekend}}W_c + \cdots + b_{\text{TTIME,HW}}(H_cW_c) + b_{\text{TTIME,YE}}(Y_cE_c) + \cdots$$

$$U_{cb}^{\text{comp}} = \gamma_{\text{MONEY}}(c)\,\text{MONEY}_{cb} + \gamma_{\text{CHARITY}}(c)\,\text{CHARITY}_{cb} + \gamma_{\text{PRODUCT}}(c)\,\text{PRODUCT}_{cb} + \gamma_{\text{LOTTERY}}(c)\,\text{LOTTERY}_{cb} + \gamma_{\text{PRIORITY}}(c)\,\text{PRIORITY}_{cb}$$

$$\gamma_{\text{MONEY}}(c) = MU_{\text{MONEY}} + MU_{\text{MONEY,young}}Y_c + MU_{\text{MONEY,old}}O_c + MU_{\text{MONEY,weekend}}W_c + \cdots + MU_{\text{MONEY,HW}}(H_cW_c) + MU_{\text{MONEY,YE}}(Y_cE_c) + \cdots$$

$$\gamma_{\text{CHARITY}}(c) = MU_{\text{CHARITY}} + MU_{\text{CHARITY,young}}Y_c + MU_{\text{CHARITY,old}}O_c + MU_{\text{CHARITY,weekend}}W_c + \cdots + MU_{\text{CHARITY,HW}}(H_cW_c) + MU_{\text{CHARITY,YE}}(Y_cE_c) + \cdots$$

$$\gamma_{\text{PRODUCT}}(c) = MU_{\text{PRODUCT}} + MU_{\text{PRODUCT,young}}Y_c + MU_{\text{PRODUCT,old}}O_c + MU_{\text{PRODUCT,weekend}}W_c + \cdots + MU_{\text{PRODUCT,HW}}(H_cW_c) + MU_{\text{PRODUCT,YE}}(Y_cE_c) + \cdots$$

$$\gamma_{\text{LOTTERY}}(c) = MU_{\text{LOTTERY}} + MU_{\text{LOTTERY,young}}Y_c + MU_{\text{LOTTERY,old}}O_c + MU_{\text{LOTTERY,weekend}}W_c + \cdots + MU_{\text{LOTTERY,HW}}(H_cW_c) + MU_{\text{LOTTERY,YE}}(Y_cE_c) + \cdots$$

$$\gamma_{\text{PRIORITY}}(c) = MU_{\text{PRIORITY}} + MU_{\text{PRIORITY,young}}Y_c + MU_{\text{PRIORITY,old}}O_c + MU_{\text{PRIORITY,weekend}}W_c + \cdots + MU_{\text{PRIORITY,HW}}(H_cW_c) + MU_{\text{PRIORITY,YE}}(Y_cE_c) + \cdots$$

Result of the Discrete Choice Model

Metric	Value
Number of observations	2080
Final log-likelihood LL(β)	-653
Null log-likelihood LL(0)	-2825
Number of parameters (k)	89
AIC	1484
BIC	1935
ρ^2	0.769
Adjusted ρ^2	0.737

Parameter	Estimates
Heavy and Bulky Product	-9,55
Familiar Product	4,64
Travel Time (min)	-1,67
Picking Time (min)	-3,64
Charity	0,9
Lottery	0,34
Priority	-4,2
Product	0,74

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Result of the Discrete Choice Model - Two survey studies (1) a control group (2) a focus group

When decisions are made in-store, incentives are evaluated through the lens of immediate effort, waiting, and task complexity.

Group	Picking VOT	Travelling VOT
Control	23 TL / min	8 TL / min
Focus (in-store)	27 TL / min	13 TL / min

Segment	Control Group	Focus Group
Students	Strong monetary effect	Strong charity & priority
Self-employed	Money dominant	All non-cash negative
Young	Lottery mildly positive	Lottery ineffective
Small child	Moderate time sensitivity	Strong aversion to delays

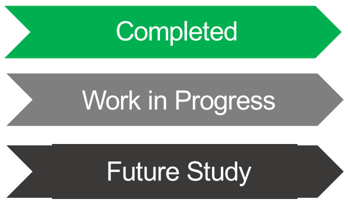
- **Control study**: Time costs are more easily tolerated.
- **In-store focus study**: time reflects **real opportunity costs**.
- Physical effort, congestion, and cognitive load **amplify time sensitivity** *(especially in focus group)*.
- **Additional insights from the focus study:**
  - ✓ Priority incentives are chosen more often
  - ✓ Non-monetary incentives become more salient
  - ✓ Customers evaluate incentives **relative to immediate effort and delay**, rather than in abstract monetary terms.

Result of the Discrete Choice Model – Segment Behavior on Different Compensation Types

- Students strongly favor **non-monetary incentives.**
  - Checkout priority is valued at nearly **1,000 TL**
- **Interest in lottery-based** incentives declines sharply with age
- **High-income** shoppers highly value **priority incentives**
- Charity incentives are perceived as 3 to 4 times more valuable than money among: (Homemakers, students, self-employed individuals)
- **Product-based rewards** are less attractive than direct monetary compensation for all segments.

Next Steps

How can behavioral estimates be embedded in a prescriptive optimization model?



Thank you !

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