Customer (Dis)honesty in Priority Queues

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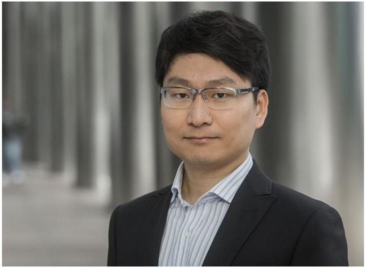
LNMB Conference 2024

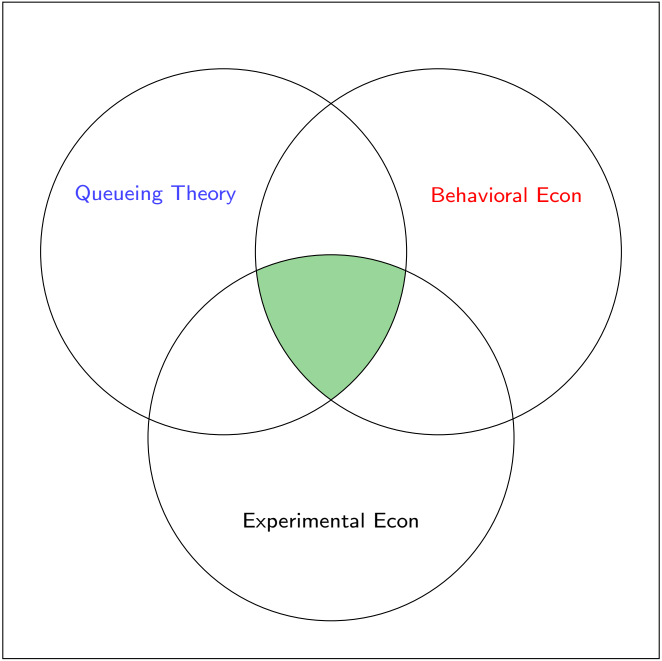
This work is joint with:

Arturo Estrada Rodriguez



Dongyuan Zhan

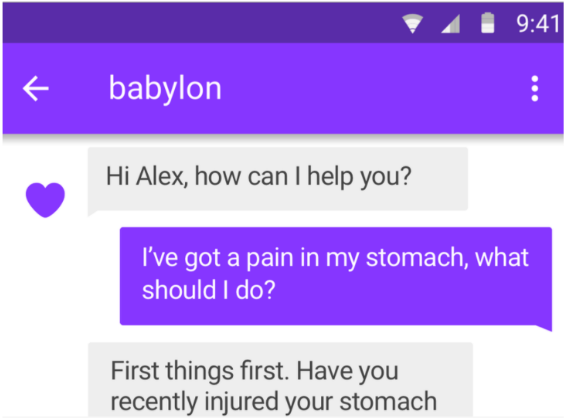
At a High Level



GP patients expected to overplay symptoms on NHS chatbot to 'get appointment quicker'

Further pilots in North West London were dropped because of fears of patients 'gaming' the system

Alex Matthews-King Health Correspondent | Thursday 23 November 2017 11:41 | comments



The chatbot app uses simulates a consultation to quiz patients about their symptoms *(babylon)*

Coronavirus: People without symptoms 'misusing testing'

9 September

Coronavirus pandemic


GETTY IMAGES

Covid: Concerns over 'queue jumping' for vaccine in London

By Guy Lynn
BBC News

24 March

Coronavirus pandemic

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- Service provider has limited resources.
- There is an incentive to lie to access service faster.
- Pricing or punishments are not applicable.
- A one-shot, anonymous, interaction with service provider.
- Queues (other people) are unobservable.

Research Questions

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1. How to model customer misreporting behaviour in queues?
    - Can our model be validated with experimental data?

2. How can we control performance in the system effectively?
    - What is the optimal scheduling policy?

Relevant Literature

- Control of queues with uncertain parameters

  Van der Zee and Theil (1961), Argon and Ziya (2009), Bren and Saghafian (2019), Singh et al. (2021)...

- Queueing economics

  Mendelson and Whang (1990), Afeche and Mendelson (2004), Kittsteiner and Moldovanu (2005), Kleinrock (1967), Lui (1985), Hassin and Haviv (2003), Hu et al. (2021), Afeche (2013), Afeche and Pavlin (2016), Yang et al. (2021), Yang (2021)...

- Misreporting behaviour

  Rosenbaum et al. (2014), Abeler et al. (2014, 2019), Fischbacher and Föllmi-Heusi (2013), Celse et al. (2019), Dugar et al. (2019), Steinel et al. (2022)...

- Behavioral queueing

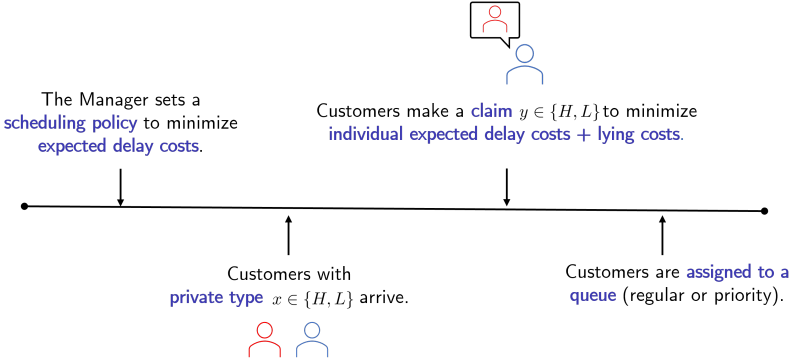
  Shunko et al. (2018), Buell (2021), Armony et al. (2021), Kim et al. (2020), Wang and Zhou (2018), Ülkü et al. (2020), Luo et al. (2022), Althenayyan et al. (2022)...

Plan for the remainder of the talk

- Part 1: Propose a queueing game model
- Part 2: Validate model experimentally
- Part 3: Design effective scheduling control

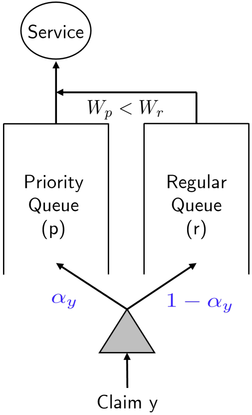
Part 1:
Queueing game model

Queueing Game: Sequence of Events



$M/M/1$ Non-Preemptive Priority Queue

Customers with a claim $y \in \{H, L\}$ are given priority with probability α_y.



Manager's Problem

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$$\underset{(\alpha_H,\alpha_L)}{Min} \; \overbrace{\sum_{x\in\{H,L\}} \lambda_{p,x}\cdot c_x\cdot\mathbb{E}[W_p]+\lambda_{r,x}\cdot c_x\cdot\mathbb{E}[W_r]}^{\text{Expected Delay Cost in System}}$$

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- $\mathbb{E}[W_p]$ and $\mathbb{E}[W_r]$ are delays in priority and regular queues.

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  - $\ell(x, x) = 0$ and $\ell(x, y) \geq 0$ for $y \neq x$.

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- Heterogeneous lying aversion: θ is a random variable.

  (Gibson et al. 2013, Rosenbaum et al. 2014, Abeler et al. 2019)

Lying Cost Models from the Literature

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Strictly convex in expected material benefit

- $\ell(x, y) = \left(c_x \cdot \left(\mathbb{E}[W | Claim = x] - \mathbb{E}[W | Claim = y] \right)^+ \right)^r, r > 1$

(Duch et al. 2021, Gneezy et al. 2018, Kartik 2009)

Best-Response Misreporting Probability

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Customer misreports when

$$c_x \cdot \mathbb{E}[W|Claim = x] \geq c_x \cdot \mathbb{E}[W|Claim = y] + \theta \cdot \ell(x, y),$$

i.e., when θ is small enough.

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$$\mathbb{P}(\text{Misreport}) = \mathbb{P}\left(\theta \leq \frac{c_x(\mathbb{E}[W|Claim = x] - \mathbb{E}[W|Claim = y])}{\ell(x, y)}\right)$$

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Later, we will show that only L customers misreport.

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Lying Cost $\ell(L, H)$	$\mathbb{P}$(Misreport)	Effect of $\Delta\alpha = (\alpha_H - \alpha_L)$	Effect of $\Delta W = (\mathbb{E}[W_r] - \mathbb{E}[W_p])$

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Linear in material benefit	$\mathbb{P}(\theta \leq 1)$	No Effect	No Effect
Convex in material benefit	$\mathbb{P}\left(\theta \leq \frac{1}{(c_L(\alpha_H-\alpha_L)(\mathbb{E}[W_r]-\mathbb{E}[W_p]))^{r-1}}\right)$	↓	↓

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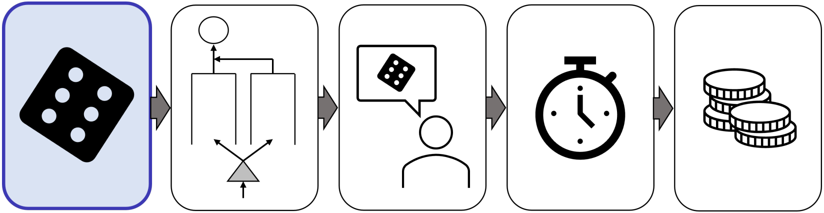
- Participants privately observe the outcome of a random variable.
- Misreporting is not detected at the individual level.
- Inferences at the aggregate level.

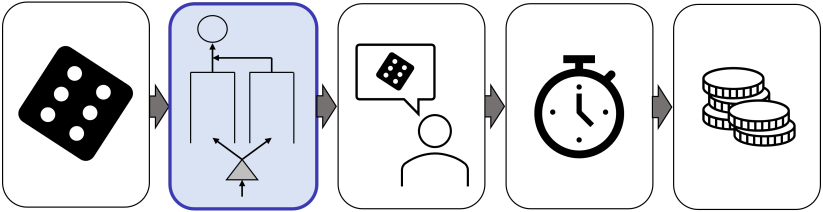
Experimental Design

We run an online experiment. Participants privately observe the outcome of a die.



Experimental Design

Participants are randomly assigned to 1 out of 9 experimental conditions that differ in their $\Delta\alpha$ and ΔW values.



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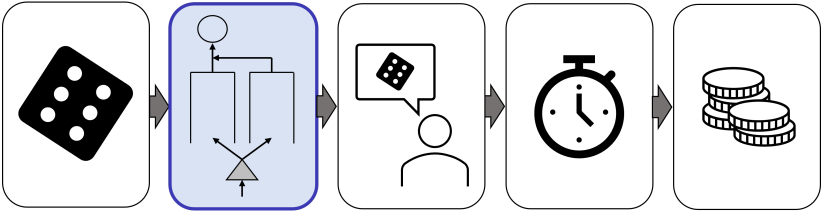
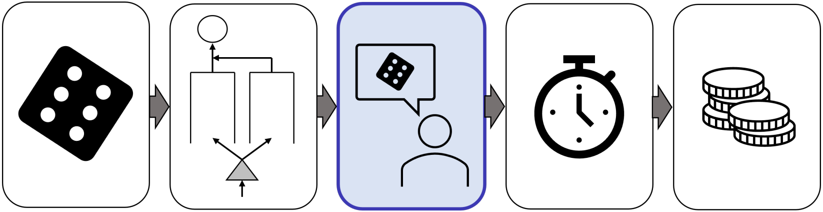


Condition	$\Delta\alpha$	ΔW	α_H	α_L	W_r	W_p	Sample size
1	1	3 min	1	0	5 min	2 min	226
2	1	8 min	1	0	10 min	2 min	220
3	1	13 min	1	0	15 min	2 min	217
4	0.5	3 min	1	0.5	5 min	2 min	222
5	0.5	8 min	1	0.5	10 min	2 min	227
6	0.5	13 min	1	0.5	15 min	2 min	222
7	0.1	3 min	1	0.9	5 min	2 min	220
8	0.1	8 min	1	0.9	10 min	2 min	233
9	0.1	13 min	1	0.9	15 min	2 min	234

Experimental Design

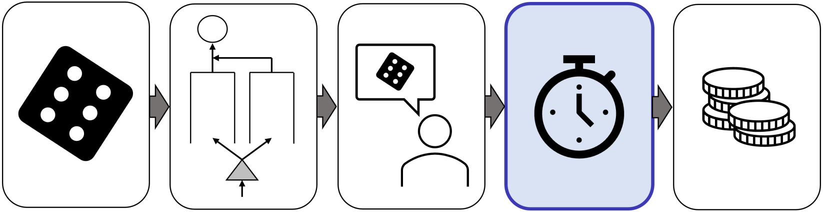
Participants make a claim about their die outcome.



- H claim: number 5.
- L claim: any other number.

Experimental Design

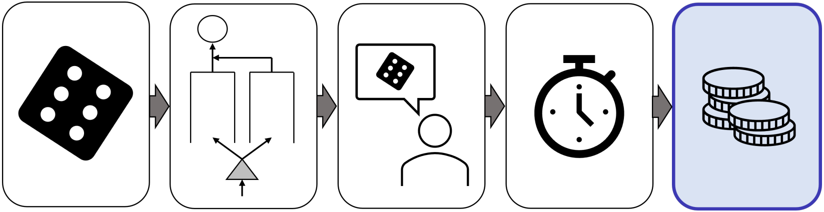
Based on participant claims and experimental condition, they wait in a virtual queue.



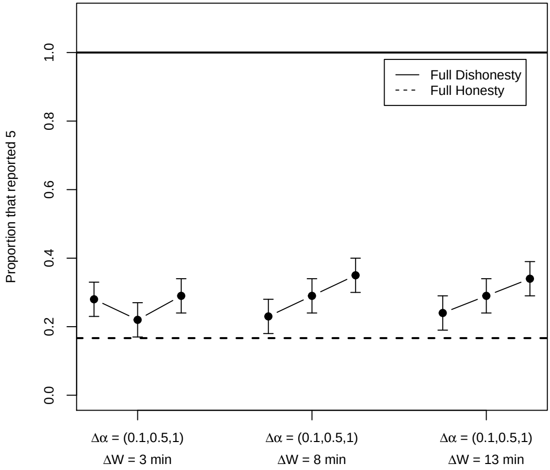
- To ensure waiting costs, participants need to click Advance in queue buttons.

Experimental Design

Participants are paid the same amount of money irrespective of their waiting time.



Experimental Results



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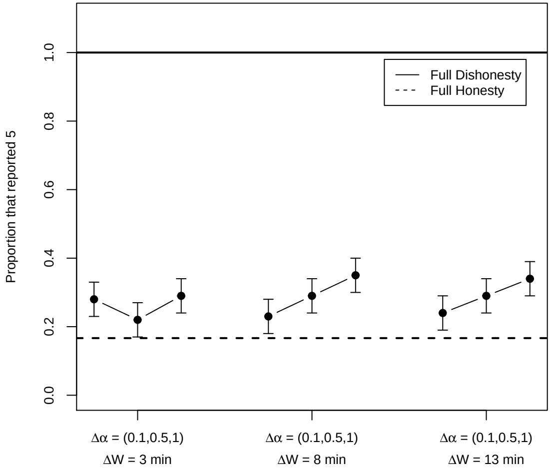

- **Result 1.** Participants misreport: Exact binomial tests against 1/6, (p-values < 0.05).

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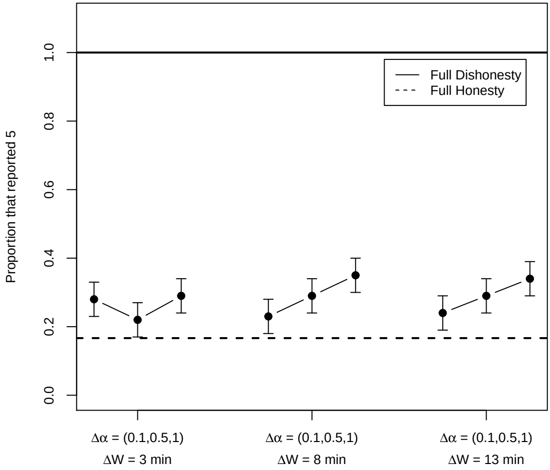

- **Result 1.** Participants misreport: Exact binomial tests against 1/6, (p-values < 0.05).
- **Result 2.** Misreporting behaviour supports the existence of lying aversion.

Experimental Results

	Logistic Regressions: $\mathbb{P}$(Claim 5)		
	(1a)	(2a)	(3a)
(Intercept)	-1.03***	-1.19***	-1.29***
	(0.21)	(0.20)	(0.22)
Age	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
GenderM	0.13	0.13	0.13
	(0.10)	(0.10)	(0.10)
ΔW	0.01	-	0.01
	(0.01)	-	(0.01)
$\Delta\alpha$	-	0.45***	0.45***
	-	(0.13)	(0.13)
N	2021	2021	2021
AIC	2398.17	2387.79	2388.81
Pseudo R^2	0.00	0.01	0.01
Pseudo R^2 †	0.01	0.23	0.25

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.
†: at aggregate level.

- **Result 3.** $\Delta\alpha$ influences misreporting behaviour.

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	(0.00)	(0.00)	(0.00)
GenderM	0.13	0.13	0.13
	(0.10)	(0.10)	(0.10)
ΔW	0.01	-	0.01
	(0.01)	-	(0.01)
$\Delta\alpha$	-	0.45***	0.45***
	-	(0.13)	(0.13)
N	2021	2021	2021
AIC	2398.17	2387.79	2388.81
Pseudo R^2	0.00	0.01	0.01
Pseudo R^2 †	0.01	0.23	0.25

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.
†: at aggregate level.

- **Result 3.** $\Delta\alpha$ influences misreporting behaviour.
- **Result 4.** ΔW does not influence misreporting behaviour.

Experimental Results

	Logistic Regressions: $\mathbb{P}$(Claim 5)		
	(1a)	(2a)	(3a)
(Intercept)	-1.03***	-1.19***	-1.29***
	(0.21)	(0.20)	(0.22)
Age	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
GenderM	0.13	0.13	0.13
	(0.10)	(0.10)	(0.10)
ΔW	0.01	-	0.01
	(0.01)	-	(0.01)
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- **Result 3.** $\Delta\alpha$ influences misreporting behaviour.
- **Result 4.** ΔW does not influence misreporting behaviour.
- **Result 5.** None of the lying-cost models from the literature exhibit the same directional patterns of the data.

Experimental Results

Lying Cost	$\mathbb{P}$(Misreport)	Effect of $\Delta\alpha = (\alpha_H - \alpha_L)$	Effect of $\Delta W = (\mathbb{E}[W_r] - \mathbb{E}[W_p])$
Fixed Cost	$\mathbb{P}(\theta \leq c_L(\alpha_H - \alpha_L)(\mathbb{E}[W_r] - \mathbb{E}[W_p]))$	$\uparrow$	$\uparrow$
Linear in material benefit	$\mathbb{P}(\theta \leq 1)$	No Effect	No Effect
Convex in material benefit	$\mathbb{P}\left(\theta \leq \frac{1}{(c_L(\alpha_H - \alpha_L)(\mathbb{E}[W_r] - \mathbb{E}[W_p]))^{r-1}}\right)$	$\downarrow$	$\downarrow$
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Why do existing lying-cost models fail to fit our data?

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Why do existing lying-cost models fail to fit our data?

Because the outcomes of lying are uncertain in our setting.

Part 3:
Scheduling Control

Updated Customer Lying Aversion Model

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$$\underset{y\in\{H,L\}}{Min} \quad \overbrace{c_x \cdot \mathbb{E}[W|Claim = y]}^{\text{Delay cost}} + \underbrace{\frac{\theta}{\tau(\Delta\alpha)}}_{\text{Lying aversion}} \cdot \overbrace{\ell(x, y)}^{\text{Intrinsic lying cost}},$$

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We make assumptions on $\tau(\cdot)$ so that we get consistency with data.

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Proposition. There is a unique equilibrium:

Manager's Scheduling Policy

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- All H types claim their type, and only some L types misreport.

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- Honor policies, which are commonly used in practice, can be optimal.
- Managers can use upgrading policy as a control to incentivize more honesty.

Thank You!

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- $\alpha_L^* > 0 \Leftrightarrow$ the misreporting probability is sufficiently sensitive to changes in α_L.