Learning on the Go:

Understanding How Gig Economy Workers Learn with Recommendation Algorithms

Park Sinchaisri UC Berkeley





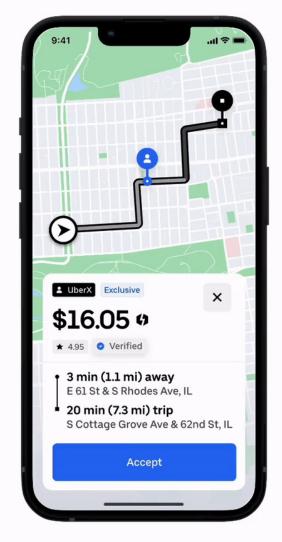


Joint work with Shunan Jiang (UC Berkeley/Google)

The Rise of the Gig Economy

- Platforms now power everyday delivery and services; 16% in US adults, 12% of global labor force
- Customers are attracted by convenience, affordable options
- Workers are attracted by flexibility and autonomy to turn work on/off, choose where/job to work

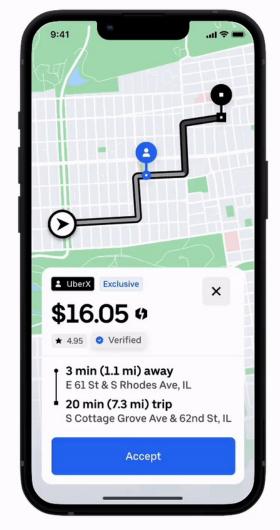




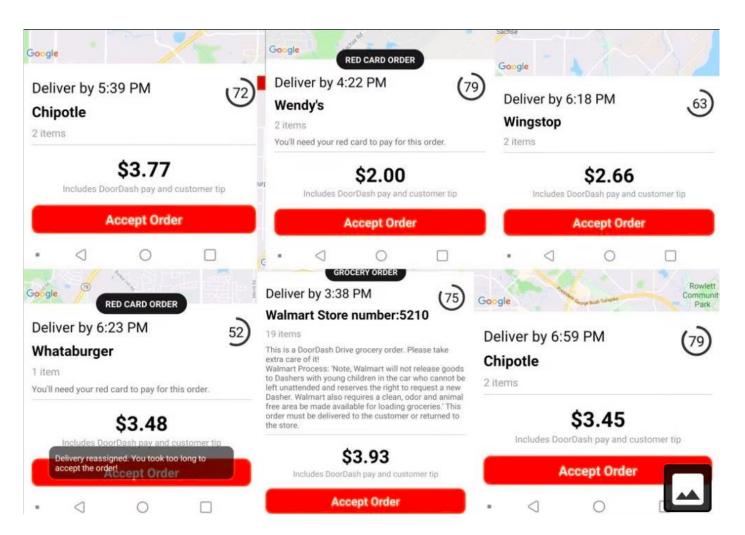
The Rise of the Gig Economy

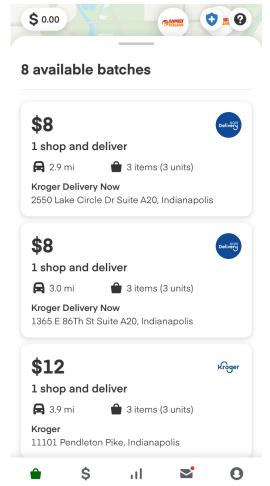
- Platforms now power everyday delivery and services; 16% in US adults, 12% of global labor force
- Customers are attracted by convenience, affordable options
- Workers are attracted by flexibility and autonomy to turn work on/off, choose where/job to work
- These choices affect service reliability + their own earnings





Focus: When Workers Choose Tasks













r/uberdrivers · Posted by u/kanyda 8 years ago

First day report

First night: 5 hours, no riders. I think I need to change my strategy.

***instacart**

Sometimes the store has long lines of people or the shopper has problems finding items.



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How to perform better on jobs?

In general, humans struggle to make optimal decisions.

(Amar et al 2011, Ibanez et al 2017, KC et al., 2020)



New Workers Struggle, But Get Better

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Tuesdays are the least profitable day of the week. The early morning (7-10) is pretty good money.

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If your shopper is slow, your order is late or might be



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Humans learn from experience

(Shafer et al 2001, Boh et al 2007, Argote 2012, Bavafa & Jónasson 2021)



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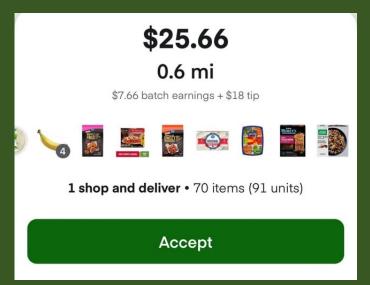
Gig workers learn differently

(Allon et al 2023, Guha & Corsten 2023, Dai et al 2024, Hernandez et al 2024)

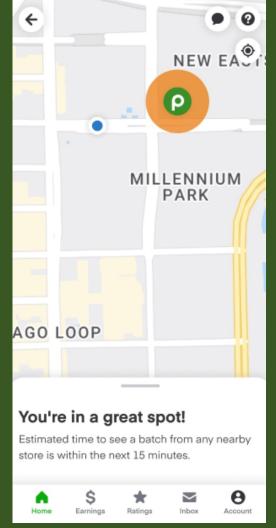


- How do workers improve performance over time?
- How does task selection change with experience?

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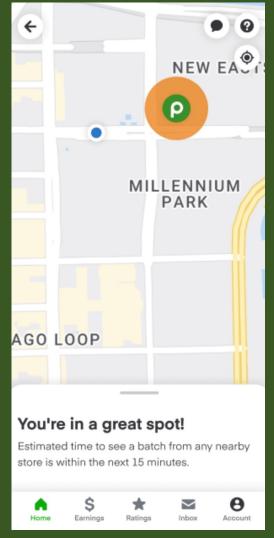


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Some benefit from them...

(Knight et al 2022, Zhang et al 2022, Do et al 2024)





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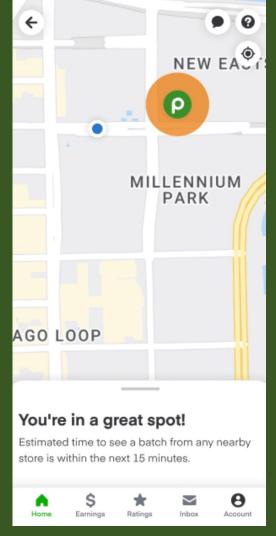
Some benefit from them...

(Knight et al 2022, Zhang et al 2022, Do et al 2024)

...but others resist

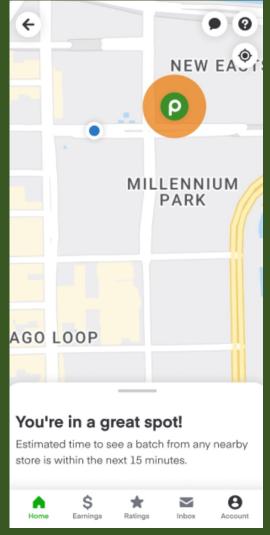
(Dietvorst el al 2015, Dietvorst et al 2018, Castelo et al 2019, Sun et al 2022, Das Swain et al 2024, Balakrishnan et al 2025, Bastani et al 2025)





- How do workers improve performance over time?
- How does task selection change with experience?
- How do workers respond to the platform's recommendations?





- NYC orders from November 2022 to October 2023
- 1,269,815 orders across 788 stores + 5,292 shoppers (1,131 "new")

- Orders: Store ID, # items, most common categories, distance to customers
- Workers: Signup hours, orders suggested to them daily, tenure with platform
- Performance: On-time delivery, customer ratings, amount of tips



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How shoppers choose tasks?

After shoppers signed up for preferred regions, platform recommends some orders. (Rec1)



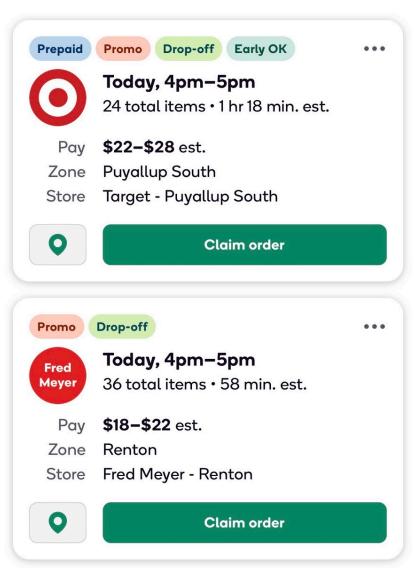
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Shoppers can choose to browse a list of all available orders



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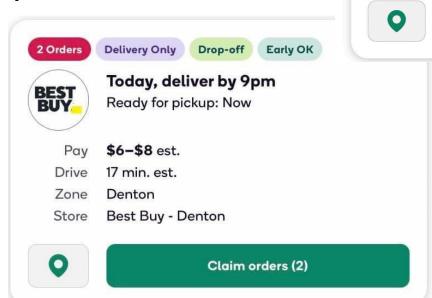
How shoppers choose tasks?





Shoppers can choose to browse a list of all available orders

Sometimes, platform bundled orders from the same store with delivery windows within 1 hour difference (Rec2)



Prepaid

\$15-\$21 est

Philadelphia

Drop-off

16 + 10 total items • 1 hr 10 min est

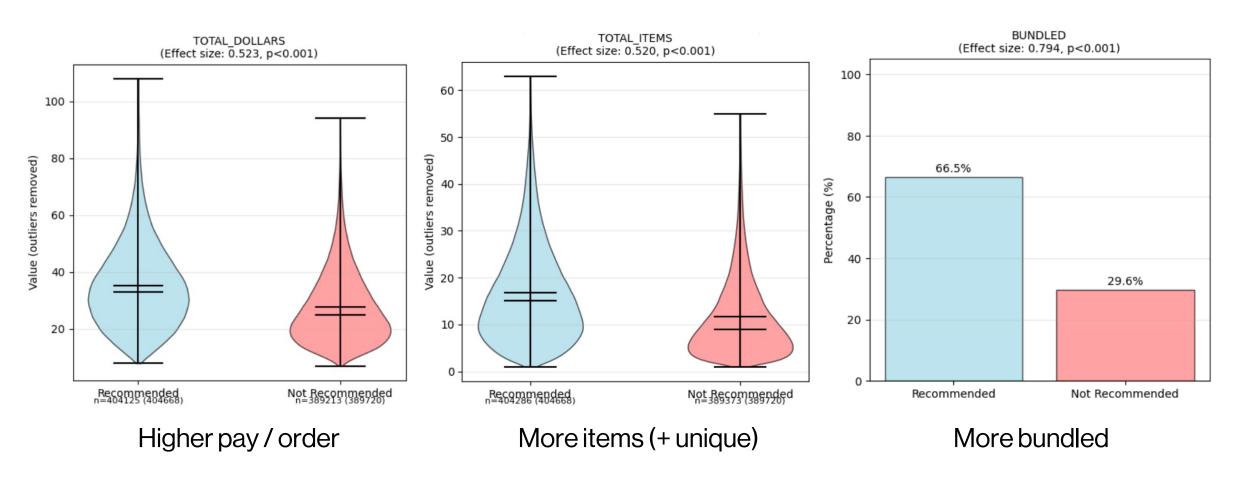
Claim orders (2)

Center City East / Southeast

Target - Philadelphia SE

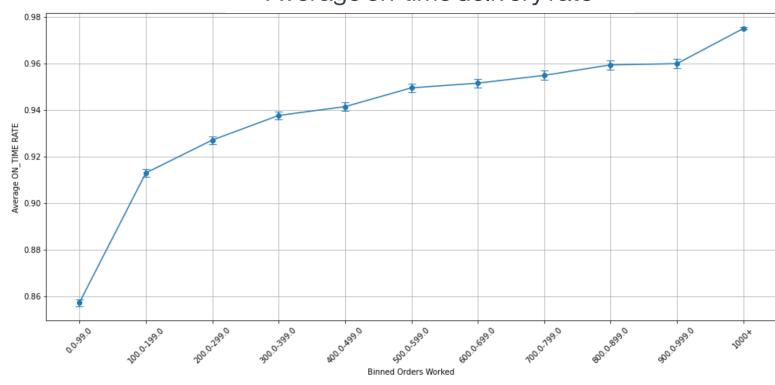
Today, 1pm-2pm

Nature of Recommended Orders

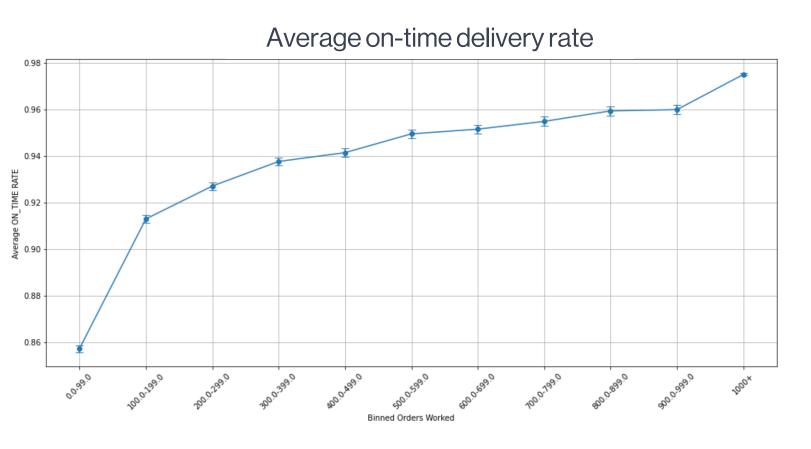


They're quite static over time!

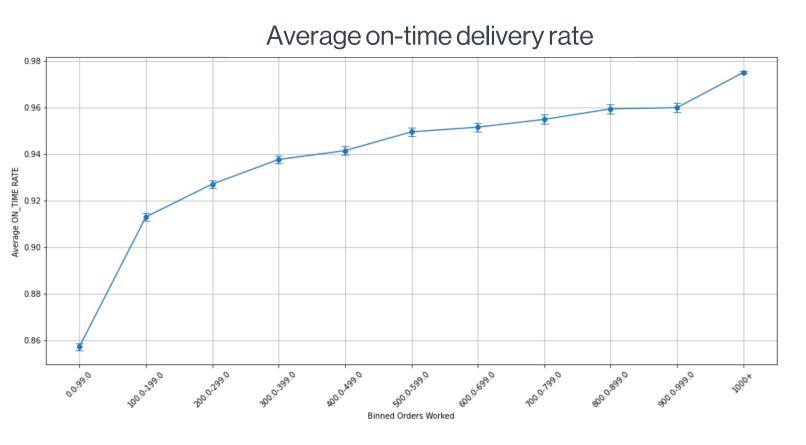




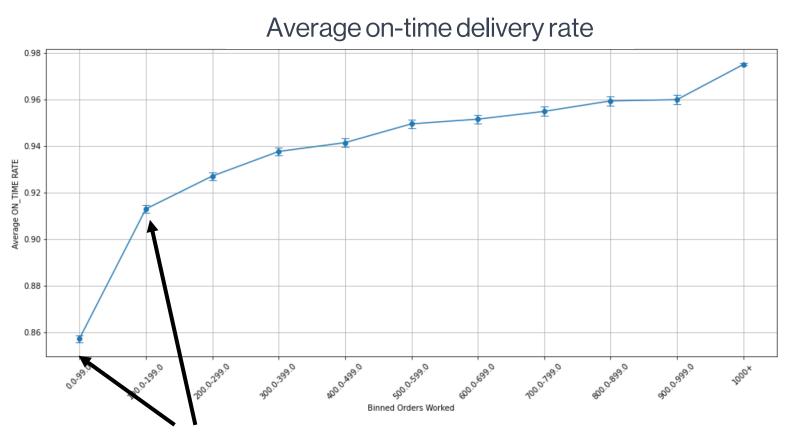
Only new shoppers who started working during the time of the data N = 1,131 shoppers



Impact on on-time	Coefficient
# Orders done from	6.0552e-05***
the same store	(0.0025236)
# Orders done from	-8.9995e-09***
the same store ^2	(1.6775e-09)
# Orders done from	5.9109e-05***
other stores	(0.0001787)
# Orders done from	-8.8744e-09***
other stores ^2	(0.0149002)
Control Variables	Yes
Individual FE	Yes
Time FE	Yes



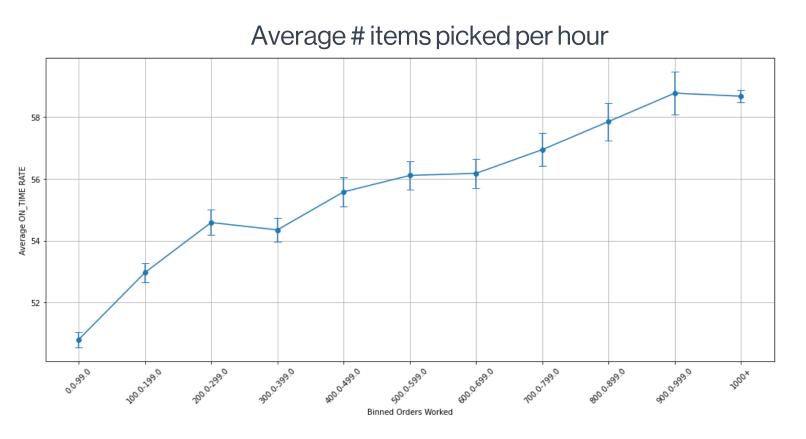
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We'll use the first 100 and 200 orders as workers' key milestones of learning

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# Orders done from	-8.8744e-09***
other stores ^2	(0.0149002)
Control Variables	Yes
Individual FE	Yes
Time FE	Yes

= 1,000 orders, 6.0% \(\gamma\)



Impact on on-time	Coefficient
# Orders done from	9.4281e-03**
the same store	(0.007595)
# Orders done from	-5.4681e-06**
the same store ^2	(0.003098)
# Orders done from	6.3414e-03*
other stores	(0.022478)
# Orders done from	-7.6253e-07
other stores ^2	(0.235005)
Control Variables	Yes
Individual FE	Yes
Time FE	Yes

Evolution of Performance

• Productivity metric: # items per hour, within the first 100-100 orders

First/Second	Low	Medium	High
Low	74.07%	22.22%	3.70%
Medium	22.22%	51.85%	25.93%
High	3.70%	25.93%	70.37%

Most shoppers stay within the same performance tiers

Evolution of Performance

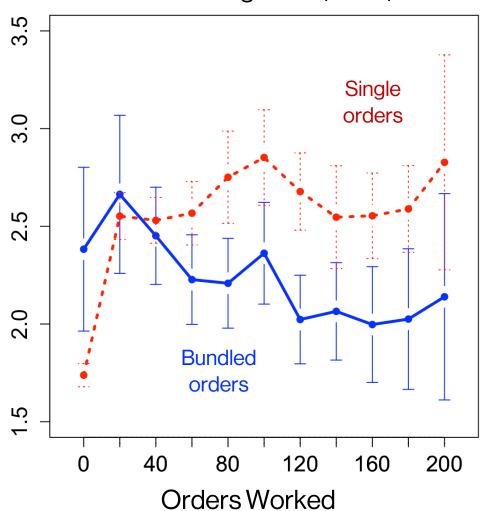
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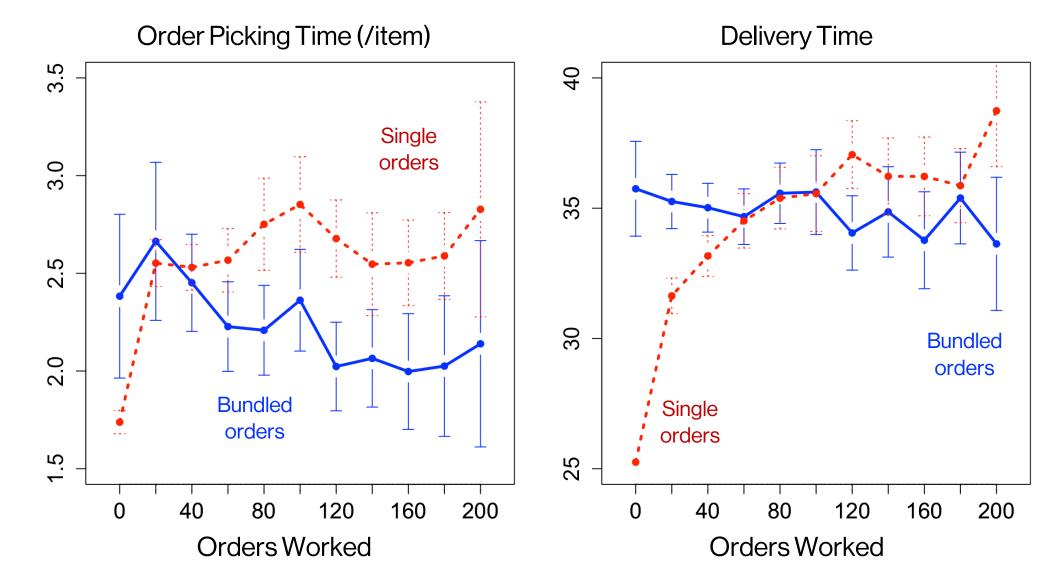
What helped low performances to get better?

How Did They Improve?

Order Picking Time (/item)



How Did They Improve?



How Did They Improve?

Start\End	Low	Medium	High	# average concurrent orders
Low-First 100	2.223500	1.925000	2.240000	
Low-Second 100	2.632000	2.333333	2.190000	

Bundling Early On Helps

Start\End	Low	Medium	High
Low-First 100	2.223500	1.925000	2.240000
Low-Second 100	2.632000	2.333333	2.190000

average concurrent orders

Initial low performers, who tried more bundling early on and adjusted down later, ended up improving performance

Bundling Moderately Early On Helps

Start\End	Low	Medium	High
Low-First 100	2.223500	1.925000	2.240000
Low-Second 100	2.632000	2.333333	2.190000
High-First 100	2.450000	2.745714	2.435263
High-Second 100	3.500000	3.315714	2.725789

average concurrent orders

Initial low performers, who tried more bundling early on and adjusted down later, ended up improving performance

Those performing poorly later on tend to be those who **over-bundled**.

What Type of Bundling?

Start\End	Low	Medium	High
Low-First 100	0.171333	0.174615	0.105000
Low-Second 100	0.228667	0.226923	0.135000

P(bundling without recommendation)

What Type of Bundling?

Start\End	Low	Medium	High
Low-First 100	0.171333	0.174615	0.105000
Low-Second 100	0.228667	0.226923	0.135000

P(bundling without recommendation)

Those doing well did less self-bundling / more platform recs.

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Start\End	Low	Medium	High	Those doing well did loss solf-
Low-First 100	0.171333	0.174615	0.105000	Those doing well did less self-bundling / more platform recs.
Low-Second 100	0.228667	0.226923	0.135000	
Low-First 100	1.141000	1.120769	1.105000	Bundles with different stores
Low-Second 100	1.166000	1.093846	1.090000	

What Type of Bundling?

Start\End	Low	Medium	High	P(bundling without recommendation)
Low-First 100	0.171333	0.174615	0.105000	Those doing well did less self-bundling / more platform recs.
Low-Second 100	0.228667	0.226923	0.135000	
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Low-First 100	1.141000	1.120769	1.105000	Bundles with different stores
				did less across-store bundling
Low-Second 100	1.166000	1.093846	1.090000	
Low-First 100	1.729000	1.819231	1.745000	Bundles with different top categories
				and did bundling moderately
Low-Second 100	1.852333	2.022308	1.950000	across different categories

After shoppers signed up for preferred regions, platform recommends some orders. (Rec1)



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The utility U_{nj} for alternative j for individual n is defined as:

$$U_{nj} = \beta_1 X_{1nj} + \beta_2 X_{2nj} + \dots + \beta_k X_{knj} + \epsilon_{nj}$$

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Recommended: 1 = recommended by platform; 0 = else

Past Frequency: proportion of all previous orders completed by the worker
that were fulfilled at the same store → Higher = more exploitation of familiar stores

Dummy group indicators: most productive (129+ orders) as reference group

All the other order information workers can see while browsing

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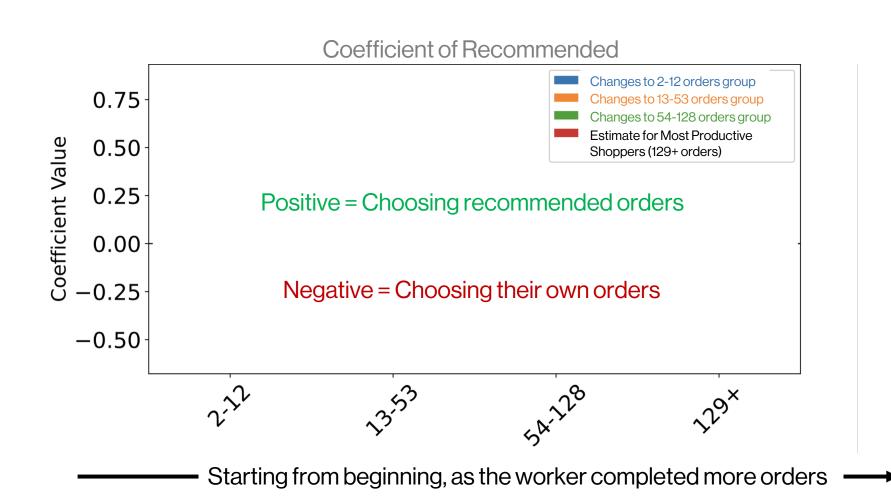
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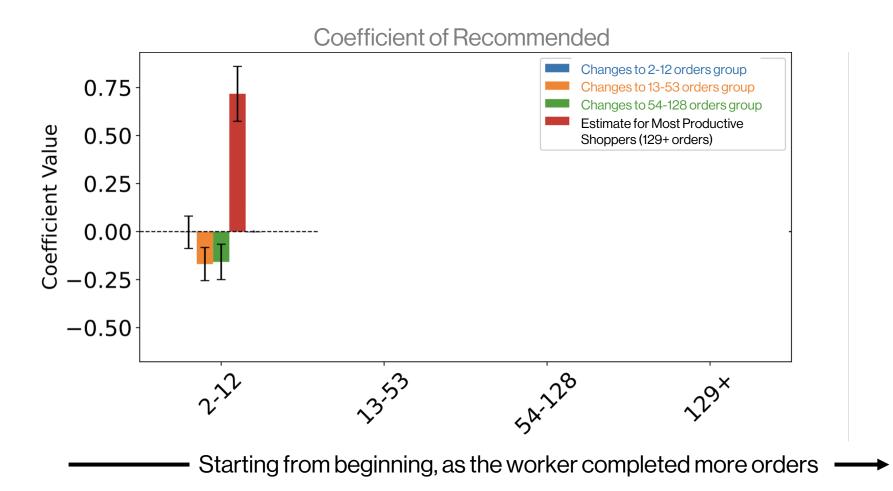
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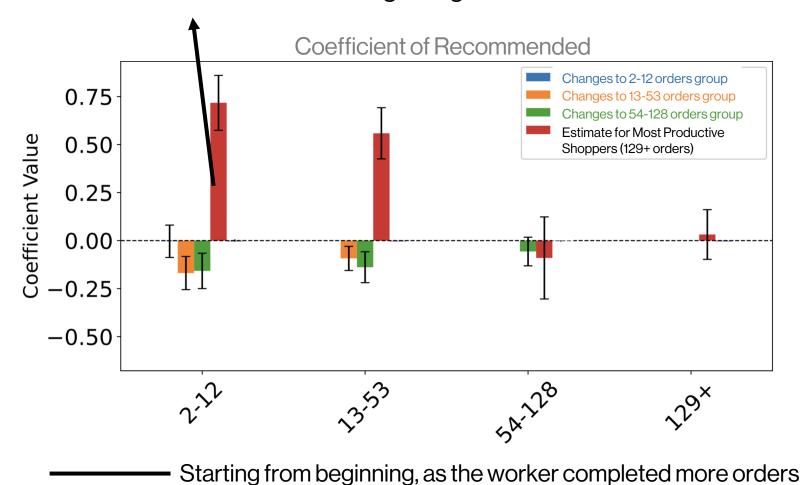
The probability that individual n chooses alternative j is given by the softmax function:

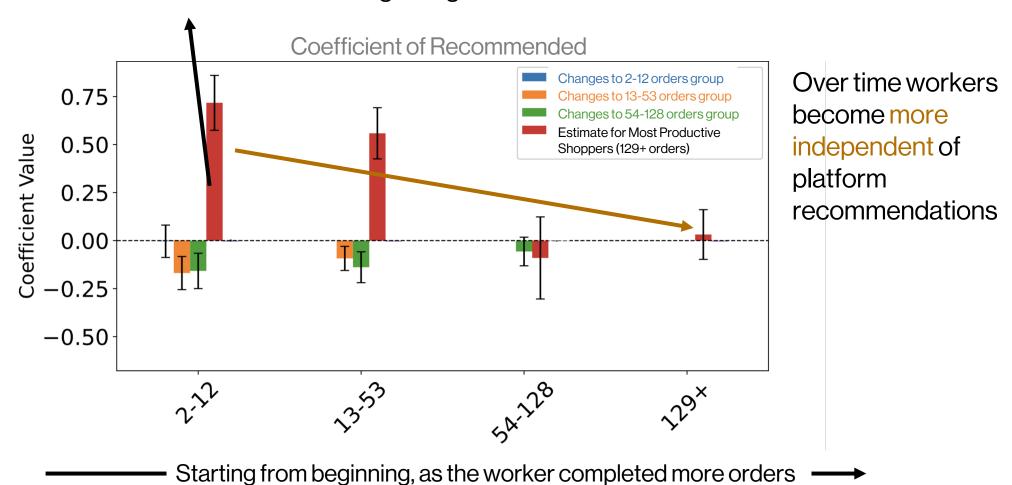
$$P(y_n = j) = \frac{e^{U_{nj}}}{\sum_{j' \in J} e^{U_{nj'}}}$$
 Multinomial Logit





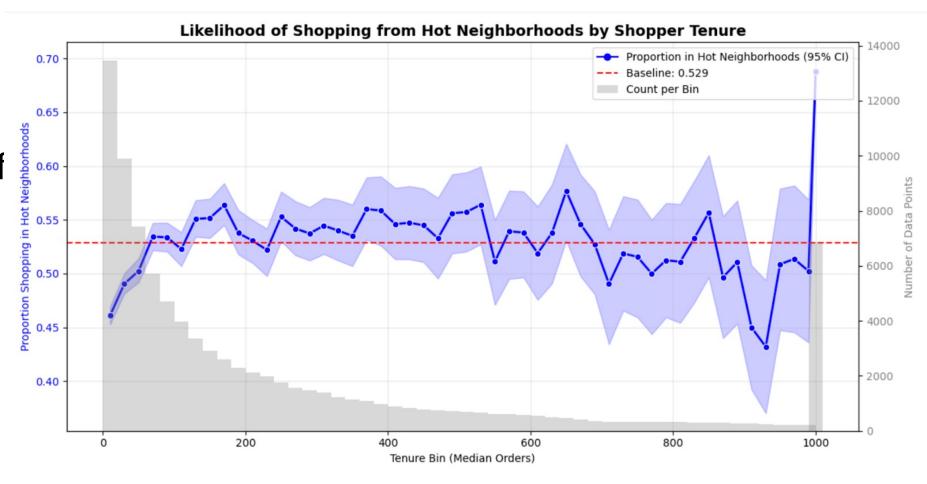






Explore Before Exploit?

We find that those doing well started off more exploitative, only exploring new stores or neighborhoods later on.



Preview: Experimental Design

. . _ .

Safeway for Charlotte

\$ 20 4 - apple
Piedmont 3 - watermelon
3 - orange

Safeway for James

\$ 20 4 - orange
Piedmont 3 - apple
4 - watermelon

Target for Jacob

\$ 20 2 - pineapple
Emeryville 9 - watermelon
2 - grape
1 - apple
3 - banana

Target for William

\$ 20 1 - banana
Emeryville 1 - apple
1 - pineapple
1 - grape
1 - watermelon

Safeway for Charlotte

\$ 20 4 - apple 3 - watermelon **Piedmont**

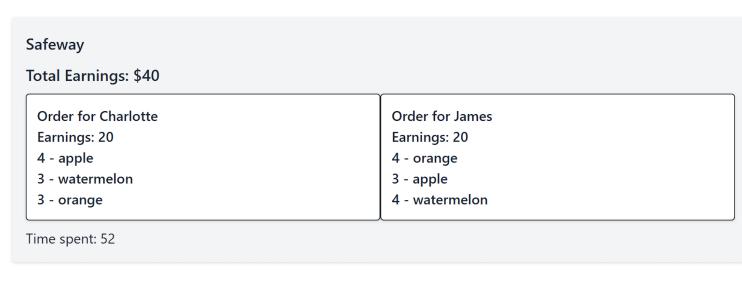
3 - orange

Safeway for James

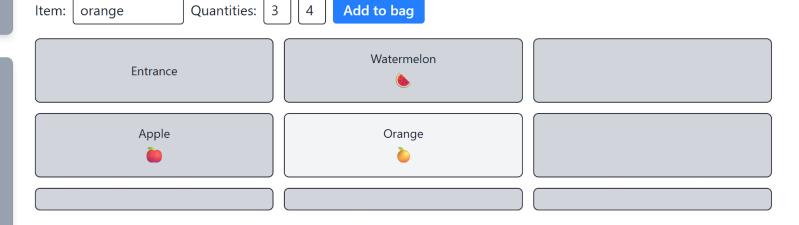
\$ 20 4 - orange 3 - apple

Piedmont

4 - watermelon



Current Location: Orange

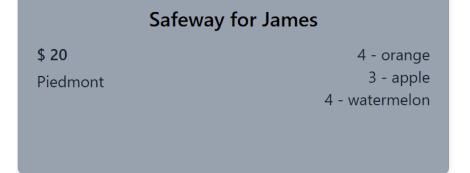


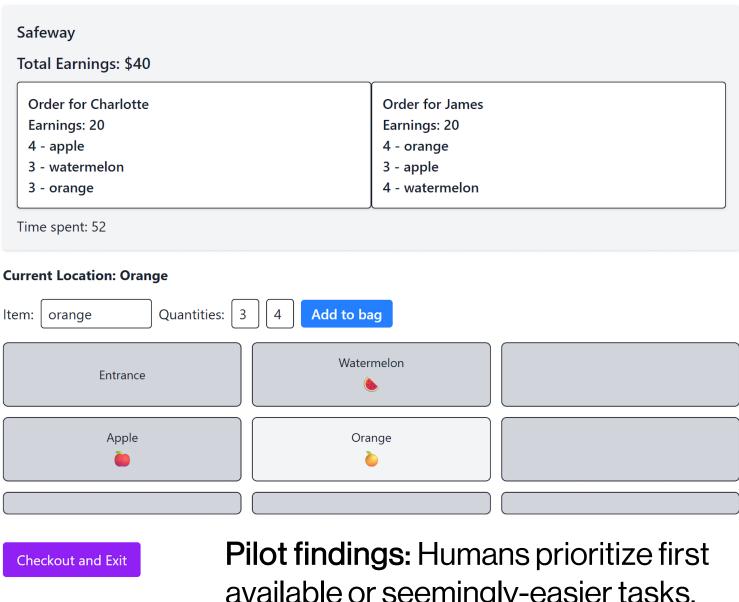
Checkout and Exit

Bag 1 Bag2

• apple: 4 • apple: 3

Safeway for Charlotte \$ 20 4 - apple 3 - watermelon **Piedmont** 3 - orange





Bag2 Bag 1 • apple: 4 • apple: 3 available or seemingly-easier tasks, similar to Ibanez et al 2017's findings!

Takeaways Learning on the Go

How gig workers choose gig tasks and learn to improve performance over time?

- Context: On-demand delivery workers in NYC, choosing own tasks, given recommendations
- Workers learn to perform better and make better decisions; workers who exploit more / rely more on platform recommendations initially improve performance the most
- Overtime workers behaviors change a lot; and they become independent of the platform's recommendation

Next Steps:

- Online behavioral experiment
- Model human learning curve + incorporate into contextual bandits
- Pilot Insights: Humans prioritize first available or seemingly-easier tasks



Thank you!

