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Transformation of Grocery Shopping and Delivery: Perspective from an Instacart Delivery Shopper

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ABSTRACT

This study investigates the economic viability of independent workers in platform-based last-mile grocery delivery systems, focusing specifically on Instacart as a representative service supply chain. While prior research has examined operational efficiency, platform-level matching, scheduling, and service performance, less attention has been given to worker-level net income viability within the operational design and cost structures set by platforms. To address this gap, we develop a hybrid simulation framework integrating discrete-event simulation (DES) and system dynamics (SD). The DES model captures order processing, shopping, and delivery operations, while the SD model represents the accumulation of earnings and costs over time. Drawing on Expected Utility Theory and Distributive Justice Theory, we model worker decision-making under uncertainty and evaluate income fairness relative to effort and cost exposure. Using empirically grounded parameters, we analyze how batch structure, store characteristics, fuel costs, and tipping behavior affect hourly net income. Results reveal substantial earnings variability and highlight trade-offs between throughput efficiency and income stability. This study contributes by introducing a human-centered perspective on last-mile delivery, developing a hybrid simulation approach for platform-based supply chains, and providing insights for platform design and compensation policies.

Keywords: *Peer-to-Peer business, Instacart, Expected Utility Theory, Discrete Event Simulation, System Dynamics Simulation*

1. INTRODUCTION

Platform-based last-mile delivery systems have become an increasingly critical component of modern supply chains, enabling retailers to extend fulfillment capabilities through decentralized, on-demand labor. Peer-to-Peer (P2P) asset-sharing businesses connect individuals in unprecedented ways through a digital platform and enable individuals to transact directly with one another (Al Mashalah, 2025; Arevalo-Ascanio, 2024; Caldieraro *et al.,* 2018; Caliskan *et al.,* 2025; Ewedairo , 2025; Puram, 2022). Such platform-based models have significantly influenced retail supply chains by accelerating digital transformation and enabling omnichannel fulfillment strategies.

Instacart, a San Francisco-based platform retail service founded in 2012, is a prominent example of a P2P asset-sharing company that provides order and delivery of groceries from participating retail stores, where independent contractors (delivery shoppers) perform both shopping and last-mile delivery tasks. Instacart operates across thousands of cities in North America and partners with a wide range of retailers, from local grocers to large chains, making it one of the most visible platform-enabled grocery delivery systems. While this model offers flexibility and scalability, it also shifts operational responsibilities and cost burdens, such as fuel consumption, vehicle depreciation, and time variability, onto workers. As a result, the economic sustainability of this workforce becomes a critical yet underexplored dimension of last-mile supply chain design.

Instacart offers flexible working hours for independent contractors who can simultaneously work for multiple platforms and adjust their schedules based on personal preferences (Lobel, 2017). Although such flexibility can attract workers to platform-based systems, the actual expenses and operational trade-offs involved in performing these services are often overlooked.

Prior research in supply chain management has examined last-mile delivery with a focus on routing efficiency, fulfillment performance, and platform coordination (Agatz *et al.,* 2025; Boyer & Hult, 2005; Park *et al.,* 2025). In parallel, studies in the platform economy and gig work literature have explored worker flexibility, compensation structures, and labor conditions (Sundararajan, 2017; Caldieraro *et al.,* 2018), tipping / driver behavior (Castillo *et al.,* 2022). Emerging work on crowdsourced delivery systems further investigates workforce scheduling and platform-level optimization (Savelsbergh & Ulmer, 2022; Ulmer & Savelsbergh, 2020). However, these research streams remain largely disconnected. In particular, existing studies do not adequately examine how operational design choices (e.g., batching, store characteristics) and cost structures (e.g., fuel consumption and vehicle depreciation) jointly determine worker-level net income in platform-based supply chains.

This gap is particularly important because grocery delivery differs from other forms of last-mile logistics. Unlike parcel or restaurant delivery, Instacart shoppers face heterogeneous store environments, varying product location information, and batch-based order structures that directly influence service time and earnings. At the same time, compensation is subject to uncertainty due to factors such as tipping behavior, platform pricing mechanisms, and fluctuating fuel costs. These conditions create a complex decision environment in which workers must balance throughput efficiency, cost exposure, and income stability.

In this paper, we examine how operational and cost factors jointly influence the net income of Instacart delivery shoppers using a hybrid simulation framework. More specifically, we analyze the conditions under which platform-based grocery delivery work can achieve income levels comparable to minimum wage benchmarks.

This study is grounded in Expected Utility Theory (EUT) and Distributive Justice Theory (DJT). EUT provides a foundation for modeling how workers make decisions under uncertainty, such as selecting batches, stores, and delivery options based on expected earnings and costs. DJT complements this perspective by framing how workers evaluate compensation fairness relative to their effort and costs. Together, these perspectives enable a behaviorally grounded, fairness-aware analysis of worker income in platform-based supply chains.

While modeling delivery operations using discrete-event simulation (DES) is relatively straightforward due to the process-based nature of the workflow, capturing the dynamic accumulation of earnings and costs requires an additional modeling perspective. DES is used to represent the operational flow of orders, shopping, and delivery activities, while system dynamics (SD) is employed to model the accumulation of earnings, fuel costs, and vehicle depreciation over time. The integration of these approaches allows us to capture both micro-level operational processes and macro-level financial dynamics, which cannot be fully represented using a single simulation method.

This study makes several contributions to the literature. First, it contributes to supply chain management by introducing a human-centered perspective on last-mile delivery, emphasizing worker income viability as a key dimension of platform-based supply chain design. Second, it advances theory by integrating EUT and DJT into a simulation-based framework, linking worker decision-making and fairness considerations to operational outcomes. Third, it contributes methodologically by developing a hybrid discrete-event and SD simulation approach that captures both operational workflows and dynamic cost accumulation. Fourth, it provides new insights into the structural drivers of income variability, highlighting trade-offs between throughput efficiency, cost exposure, and earnings stability in crowdsourced delivery systems. Finally, the findings offer implications for platform design and policy, particularly in relation to compensation structures and minimum wage considerations.

The paper is organized as follows. Section 2 provides a review of the relevant literature and theoretical basis of the study, followed by Section 3 which discusses the research methodology. Sections 4 and 5 present the research findings and discussion, while Section 6 provides conclusions, research limitations, and future research proposals.

2. LITERATURE REVIEW

2.1 Peer-to-Peer (P2P) Asset Sharing

In the literature, different definitions were used for sharing economies, such as collaborative consumption/collaborative economy (Castillo, 2022; Lessig, 2008; Park, 2022; Puschmann and Rainer, 2016), access economy/access-based consumption (Agatz, 2025; Bardhi and Eckhardt, 2012; Boyer, 2005; Gobble, 2017), on-demand economy (Berg, 2015), platform economy (Kenney and Zysman, 2016), crowd economy (Chaudhari and Sinha, 2021; Sundararajan, 2017), P2P economy/P2P asset sharing (Einav *et al.,* 2016; Hamari *et al.,* 2016; Klein *et al.,* 2022; Savelsbergh , 2022; Ulmer, 2020; Weber, 2016; Wilhelms *et al.,* 2017; Wirtz *et al.,* 2019). Eckhardt *et al.* (2019) defined common features of the above definitions for sharing economy with these five characteristics – access-oriented, economically substantive, technology based matching platform, crowdsourced supply and two traits - reliance on a reputation system and a peer-to-peer relationship. In this study, we used the terminology of P2P asset sharing, which can be considered as service innovation (Wirtz *et al.,* 2019) in the sharing economy, refers to the connection of resource providers and customers through community-based digital platforms (Hamari *et al.,* 2016) to transact directly with one another (Caldieraro *et al.,* 2018). The digital platforms mediate this transaction between resource providers and consumers in which both sides have limited access for a given period of time to these platforms for free or for a fee through the internet (Frenken and Schor, 2017; Klein *et al.,* 2022).

P2P asset sharing is a fast-growing platform-based business that provides services in a wide range of areas, including food/grocery/package delivery, ride-hailing, accommodation, investments, etc. Advances in mobile and business intelligence technologies, particularly in artificial intelligence, machine learning, analytics, and data mining, have stimulated the growth of platform-based businesses to support or meet changing consumer preferences and consumption patterns (Wirtz *et al.,* 2019). These platforms enable renting or sharing assets on a short-term basis by connecting owners, who act as independent agents, with customers (Benjaafar & Hu, 2020), fueling the P2P businesses' rapid growth.

Platform-based businesses offer flexible working hours for their self-contractors. These individuals can simultaneously work for different companies and possess the flexibility to make their working schedules. They can devise their working schedules varying from a 50-hour workweek or more to occasional work for several hours on the weekend to earn extra money in addition to another income derived from wages or fringe benefits (Lobel, 2017).

The conceptual analysis for other forms of collaborative consumption, such as access-based services, renting, or buying, has built a basis for P2P research (Ertz *et al.,* 2019). In recent years, academic research related to P2P asset sharing has proliferated, alongside the use of platform services (Ozkan & Ward, 2019). Many of these studies focus on ridesharing services (Cohen *et al.,* 2022; Hu & Zhou, 2018; Idug *et al.,* 2023; Ozkan & Ward, 2019). For instance, Wilhelms *et al.* (2017) investigated the incentives of consumers to provide P2P car sharing services. On the other hand, Münzel *et al.* (2019) investigated P2P car sharing from the perspective of users' motives, rather than asset providers. Furthermore, Benoit *et al.* (2017) explored a triadic framework for motives of collaborative consumption within platform providers (e.g., Lyft), service provider (Lyft driver), and customer service. In another study of actor-specific analyses of asset providers, Philip *et al.* (2015) explored temporary disposition and acquisition of P2P renting. More recently, Idug *et al.* (2024) examined how rider–driver ethnicity match/mismatch shapes satisfaction, willingness to perform, and trust in the ride-hailing context, highlighting the role of social-identity dynamics in P2P service interactions.

Nevertheless, because of the relative novelty of the topic, research on the phenomenon of shared economies and their applications for online grocery is sparse and overlooks the labor/worker side of P2P sharing. This is especially true regarding the variety of store types influencing delivery time and financial factors, such as payments, tips, and hidden costs, a factor not yet quantified in grocery delivery contexts, affecting workers' preferences. While most studies in this area focus on technological innovations, customer adoption, and service quality (Huynh, 2023; Jiang, 2021), there is little or no research on payment models, platform structure, and store variability. Furthermore, to the best of our knowledge, there is no study that aims to explore the impact of P2P online grocery delivery shopping jobs on minimum wage worker income and study this pre- and post-minimum wage increase to $15 per hour by employing a DES model linked to a SD model. This paper represents an effort to fill these gaps.

2.2 Theoretical Basis

The theoretical basis of this study relies on the perspective of DJT and EUT.

2.2.1 Distributive Justice Theory (DJT)

DJT argues that the rule of equity, which is an expectation of a fair distribution of rewards, should be promoted by companies in allocating compensation that reflects the value of an individual's relative contribution to the economic activity (Colquitt *et al.,* 2001; Greenberg, 1990). The distributive justice framework contends that when P2P workers perform essential tasks, especially during times like the Covid-19 pandemic such as delivering health supplies or groceries to hospitals, essential workers, etc, the economic reward for the labor should reflect the perceived value of the service that is provided to the requesting party based on the justice rule (Rupp *et al.,* 2017; Shao, 2022). Using Adams (1965) framework, we operationalize perceived fairness as the ratio of net hourly income to total hours worked. DJT predicts that if this ratio falls below a certain threshold, such as the minimum wage in our case, the workers will not participate in the system. Our simulation tests this prediction directly, where this ratio falls below the minimum wage; it generates attrition as laid out in the platform literature. We also extend the DJT literature by including the procedural justice following Colquitt *et al.* (2001), who argues that in addition to the outcomes, unless the procedure to determine the algorithms are not transparent to workers, such as how the batch is calculated, they can still exit the platform.

Furthermore, it may lead to cognitive dissonance, a mental discomfort state people experience when they have conflicting or incompatible beliefs, attitudes, or behaviors (Festinger, 1957). Accordingly, workers experiencing inequity due to underpayment may respond with counterproductive work behaviors such as reducing their efforts, communicating to customers in a discourteous manner, providing incomplete food delivery, or posting negative comments on social media with the intent to harm the online platform's reputation. DJT thus conceptually urges an equitable share of rewards between the platform and the worker to eliminate these negative implications and ensure a stable resource for the company.

2.2.2 Expected Utility Theory (EUT)

EUT predicts that workers will choose a higher payoff when the costs are constant and choose lower uncertainty if the payoffs are equal (von Neumann & Morgenstern, 1947). In our simulation, we test the uncertainty situation, where store B provides aisle-level information minimizing the uncertainty for search time and effort. In line with the EUT, our results show that workers operating in Store B achieve higher net income not as a consequence of pay difference but because of the minimized uncertainty generating a more efficient batch selection. Thus, drawing from EUT, platforms that consider these factors would end up with more capacity, driver retention, and efficiency as they capture the algorithm of the driver.

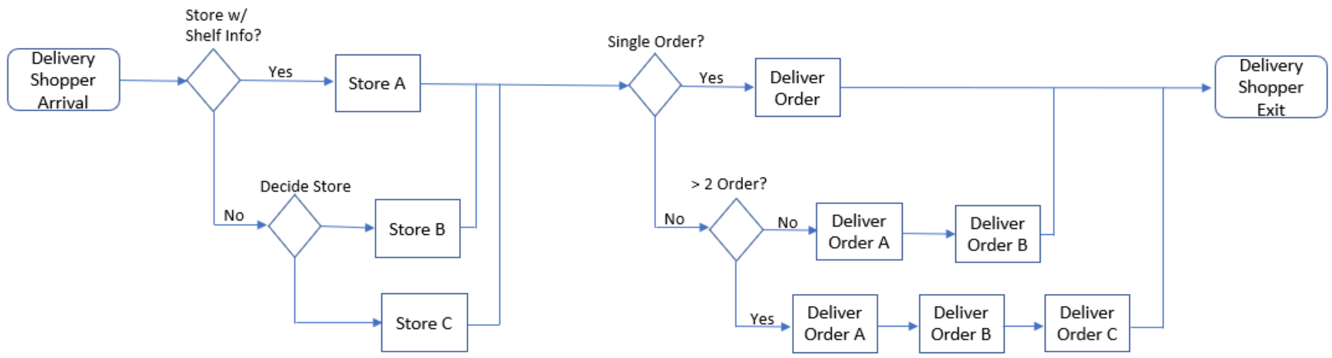

Figure 1 Discrete Event Model

Table 1 Store Information

Store Type	Provided Location Information	Relative Size
Store A	Shelf-level details	Large
Store B	Aisle-level details	Small (about half of A and C)
Store C	General location descriptions	Large

3. METHODOLOGY AND ANALYSIS

3.1 *Benefits of Employing Simulation*

The simulation approach has demonstrated its value as an effective technique for examining capacity decisions (Pujawan,2015), risk management (Oliveira, 2019) and supply chain design (Ivanov, 2019) that is efficient for problem-solving in the operations management domain (Baalsrud, 2024; Penazzi, 2017; Simchi–Levi *et al.,* 2018). Since it is very costly and not practical to make measurements via active Instacart delivery shoppers, we have employed simulation and modeling techniques. Besides, simulation and modeling are vital for a comprehensive understanding of the Instacart delivery shoppers' workflow. We use real data from a very limited number of completed deliveries by an Instacart delivery shopper to set the basic statistics to be used in simulation and modeling.

Furthermore, as mentioned above, we have a very complex model to be solved analytically. This complexity emerges due to the existence of many variables and inherent uncertainty that affects total service time and earning from a batch. Simulation design is useful to capture the complexity and dynamics of the workflow of an Instacart delivery shopper.

3.2 *Simulation Designs*

In this study, we employed two simulation methods through AnyLogic software: DES and SD. As Brailsford *et al.* (2019) note, real-world systems are complex, so a single method is often insufficient to capture their full complexity. Morgan *et al.* (2017) proposed a toolkit for combining DES and SD, which guided our sequential modeling approach. As Tako and Robinson (2012) point out, DES is well suited for transportation and delivery problems. Accordingly, DES was used to capture the step-by-step delivery process including batch selection, store navigation, shopping, and delivery, determining how long each order took and contributed to earnings and costs. The outputs of the delivery process are then passed into a SD model, which calculates net earnings over time using Instacart pay and tips as income, fuel use and vehicle depreciation as costs.

Since Instacart is one of the fast-growing P2P asset-sharing companies embracing 600,000 shoppers (Statista, 2024), in this study, it is used as the platform provider within P2P for our research setting. Due to space constraints and the model's complexity, we explain the model in general terms. We have used the discrete event distribution to simulate the process of Instacart delivery shopping (Figure 1). Multiple batches appear on an Instacart delivery shopper's phone screen, depending on the time of day. Delivery shoppers make a selection of stores based on the availability of products' location information. Instacart provides shelf information of products for some stores, making it easy for an Instacart delivery shopper to find the ordered items. In this model, we have determined three store types: Store A has shelf information, Store B has aisle information, Store C provides a more general description of products' location.Moreover, Store B's size is almost half of Store A and C (Table 1).

After checking out from stores, the Instacart delivery shopper starts the delivery based on order type. Batches may contain from a single to three orders.

The SD model has been linked to the discrete event model to compute net earnings (Figure 2). We have used data produced by the discrete event model as input to the dynamic variables (InstaPay, CustomerTip_Aggregated, FuelCost, and DepreciationCost) used in the SD model to compute earnings and costs. We have computed the net earnings by subtracting the costs incurring from the depreciation of vehicle and gas consumption from the earnings from Instacart payment and customer tips.

The shopper arrival rate is deemed a binomial distribution with eight batches per day since the average time for one batch lasts about 1 hour. The probabilities of determining stores and order types are computed by the data we have acquired. The triangular distribution is used for shopping and delivery times.

Tabel 2 Data Structure

#	Store Type	Order Type	# Items	# Units	Batch Acceptance Time	Shopping Start Time	Drop Off Time	Delivery Distance to Customer 1	Delivery Time from Customer 1 to 2	Delivery Distance to Customer 2	Delivery Time from Customer 2 to 3	Delivery Distance to Customer 3	Instacart Payment
1	B	3	28	38	10:48	11:02	12:07	2.3	7	2.3	6	2.5	$9.54
2	C	1	16	16	15:00	15:00	15:57	7.1	0	0	0	0	$12.83
3	A	1	28	28	12:36	13:07	13:47	5.1	0	0	0	0	$8.16
4	A	1	25	52	12:05	12:26	14:27	3.9	0	0	0	0	$10.65
5	A	2	42	70	14:17	14:50	16:18	2.1	17	5.5	0	0	$19.74
6	A	2	43	63	15:00	15:12	16:20	1.1	14	5.6	0	0	$11.72
7	A	2	22	41	16:34	16:45	17:40	2.1	0	2.7	0	0	$22.50
8	A	1	51	87	7:25	7:39	8:46	1.8	0	0	0	0	$17.43
9	A	1	89	146	6:01	6:22	8:16	8.4	0	0	0	0	$29.43
10	A	2	31	39	11:53	12:21	13:36	2.3	14	5.9	0	0	$10.76
11	A	1	26	49	13:41	13:48	14:49	1.8	0	0	0	0	$11.28
12	C	1	10	10	15:33	15:38	16:42	17.2	0	0	0	0	$20.94
13	A	1	36	52	8:22	8:49	10:34	15.7	0	0	0	0	$16.00
14	A	1	31	56	13:10	13:29	15:01	5.1	0	0	0	0	$17.78
15	A	2	27	45	15:10	15:34	17:20	13.8	0	0	0	0	$13.74
16	A	2	53	92	11:37	12:11	14:30	0.6	14	2.7	0	0	$21.40
17	A	1	31	37	11:38	12:08	13:13	3.4	0	0	0	0	$22.66
18	B	2	32	57	7:02	7:18	8:48	5.5	0	9.5	0	0	$15.27
19	B	1	33	45	9:18	9:29	10:22	15.8	0	0	0	0	$20.46
20	C	1	27	29	10:23	10:33	11:54	14.6	0	0	0	0	$21.25
21	A	1	5	12	18:21	18:43	19:06	2.3	0	0	0	0	$14.36
22	A	1	35	52	12:12	12:43	13:59	0.7	0	0	0	0	$7.00
23	A	2	21	26	14:08	14:11	15:00	3.4	5	1.2	0	0	$7.24
24	A	1	52	69	15:07	15:24	16:42	8.3	0	0	0	0	$18.78
25	C	1	9	13	11:26	11:33	12:22	14.7	0	0	0	0	$11.37
26	A	2	47	64	8:55	9:11	10:32	2.5	10	2.9	0	0	$11.00
27	A	3	22	41	6:01	6:21	7:17	0.5	10	3.8	8	2.3	$13.88
28	A	1	19	63	7:36	7:56	8:42	1.6	0	0	0	0	$13.04
29	B	1	30	40	8:46	9:02	10:05	3.1	0	0	0	0	$7.40
30	A	1	39	55	16:39	16:40	17:53	9	0	0	0	0	$12.27
31	B	3	38	43	7:02	7:16	8:16	2.8	10	2.3	14	5	$12.77
32	A	1	20	35	15:18	15:48	16:28	3.7	0	0	0	0	$11.46
33	B	2	30	47	16:49	16:52	18:14	5.6	0	0	0	0	$10.52
34	A	2	41	66	7:32	7:47	8:53	0.8	10	2.7	0	0	$9.60

Tabel 2 Data Structure (*Cont'd*)

#	Store Type	Order Type	# Items	# Units	Batch Acceptance Time	Shopping Start Time	Drop Off Time	Delivery Distance to Customer 1	Delivery Time from Customer 1 to 2	Delivery Distance to Customer 2	Delivery Time from Customer 2 to 3	Delivery Distance to Customer 3	Instacart Payment
35	B	1	37	51	16:04	16:36	18:18	3.4	0	0	0	0	$13.20
36	A	1	45	73	6:25	6:48	8:05	3.1	0	0	0	0	$14.75
37	A	2	37	47	8:57	9:02	11:34	4.6	41	19.8	0	0	21.35
38	C	1	10	10	11:41	11:52	12:34	13.6	0	0	0	0	10.78
39	C	1	20	20	13:00	13:02	14:12	13.6	0	0	0	0	19.65
40	A	2	47	57	6:07	6:25	8:16	9.6	14	6.5	0	0	17.75
41	A	1	49	69	8:38	8:47	10:13	2.3	0	0	0	0	14.54
42	C	2	12	15	10:12	10:40	11:58	17.1	19	10.4	0	0	24.59
43	A	1	10	15	13:51	14:08	14:51	2.4	0	0	0	0	7.42
44	B	1	19	22	14:59	15:19	16:46	13.7	0	0	0	0	12.13
45	A	1	27	38	8:16	8:49	10:07	3.7	0	0	0	0	12.37
46	B	2	30	57	10:35	11:00	11:55	2.1	10	3.7	0	0	9.5
47	A	1	42	55	12:29	12:48	14:00	1.6	0	0	0	0	15.7
48	A	2	22	25	14:00	14:06	15:13	1.8	15	6.4	0	0	9.44
49	A	1	50	90	6:26	6:45	7:55	3.8	0	0	0	0	11.06
50	B	3	24	31	8:13	8:19	10:40	44	13	7.1	16	7	15.96
51	A	1	22	32	14:07	14:27	16:49	5.6	0	0	0	0	15.29
52	A	2	46	65	16:49	17:00	18:53	3.4	26	11.9	0	0	17.21

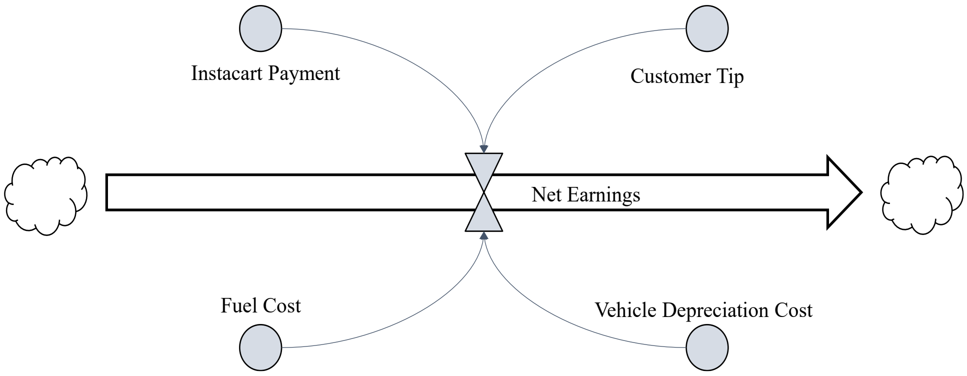

Figure 2 System Dynamics Model

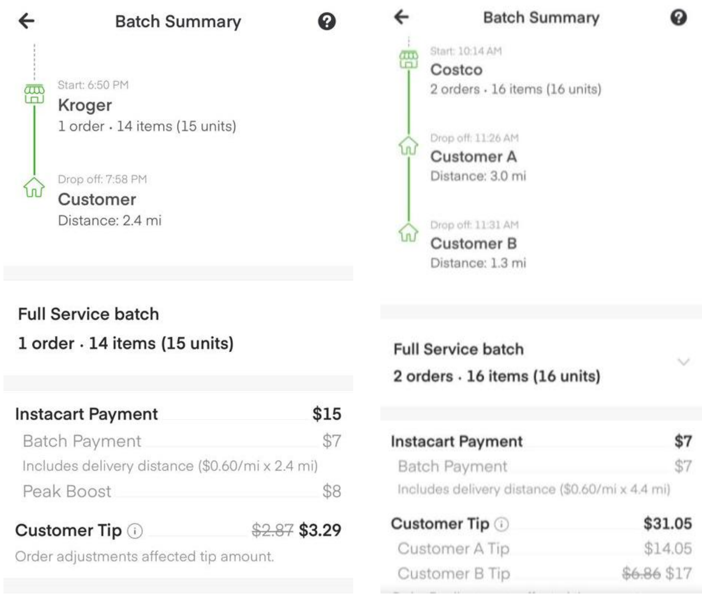

Figure 3 Instacart Delivery Shopper App Screens

Table 3 Regression Results

Model	Predictor	B	Std. Error	Beta	t	Sig.
1	(Constant)	2.264	.995		2.275	.049
	Delivery_Distance	1.902	.112	.985	17.038	.000

Note. Dependent variable: Delivery_Time.

3.3 Dataset

We have developed the Instacart shopping and delivery model based on empirical data acquired from the Instacart application of a delivery shopper in the Dallas area. Instacart delivery shopper app (Figure 3) provides information on the store type, order type, number of items and units in each order, batch acceptance time, shopping start time, drop off times to each customer, delivery distances to each customer, Instacart payment, and customer tip.

Nevertheless, the application does not provide data for the shopping end time and delivery time for customer 1. Instead, this information is given as the total shopping time and delivery time for customer 1, as illustrated in the data structure (Table 2). Furthermore, the dataset does not provide actual shopping time while providing shopping start time, drop-off times, and delivery distances. Actual shopping time is necessary to find Instacart delivery shopper's shopping speed at each store to compare store types based on their effect on the Instacart delivery shopper's net earnings. To find the actual shopping time, first, we needed to compute the delivery time to customer 1.

We have calculated delivery time to customer 1 and shopping time for each store type using the data of shopping start time, drop off time to each customer, and delivery distance to each customer. We have assumed that delivery time from customer 1 to customer 2 is similar to delivery time from store to customer 1 since the activities involving the delivery (traveling and dropping off groceries) are the

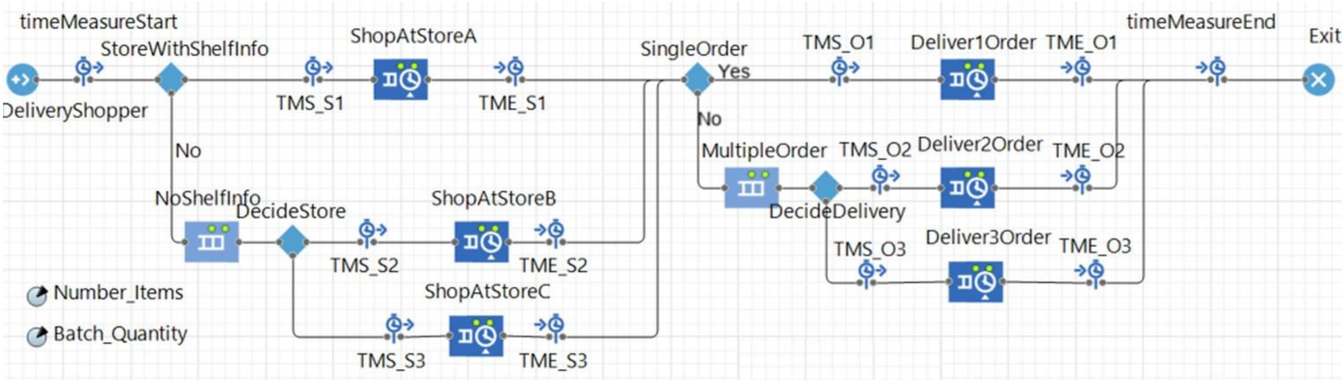

Figure 4 Instacart Delivery Shopping Process Model

same. To compute the delivery time from store to customer 1, we have conducted a simple linear regression analysis using delivery distance from customer 1 to customer 2 as a predictor and delivery time from customer 1 to customer 2 as a predicted variable.

Based on the regression results (Table 3), delivery distance from customer 1 to customer 2 is a statistically significant predictor of delivery time from customer 1 to customer 2, which includes travel and drop-off times. Using the regression equation, we have computed the delivery time to customer 1, which has not been provided by the Instacart delivery shopper application. We have calculated the total time spent at each store using the data provided by the application and the delivery time to customer 1 we have computed. Using the number of cases for each store type, we have calculated the probability of our Instacart delivery shoppers shopping at each store type. Similarly, using the total time spent at each store and the number of items shopped for each case, we have calculated the shopping speed per item at each store type.

Although our dataset is drawn from a single Instacart shopper operating in the Dallas area, it provides a rare, granular, and verified record of completed batches, including store types, item counts, batch acceptance times, shopping start times, drop-off times, delivery distances, Instacart payments, and customer tips. Operational-level data of this kind are difficult to obtain due to platform-side data restrictions and limited researcher access to shopper accounts. The purpose of this study is not to produce population-level earnings estimates but to illustrate the structural dynamics and cost sensitivities faced by a representative Instacart shopper. The simulation framework is well suited to this purpose, as it allows the parameter inputs derived from the dataset to be systematically varied to reflect a wide range of operating conditions.

3.4 Simulation Models

We used multi-method modeling to investigate how P2P online grocery shopping jobs improve minimum-wage workers' income before and after the minimum wage increased to $15 per hour. We simulated shopping using a DES model and integrated it with an SD model to estimate Instacart shoppers' net income after deducting hidden costs from Instacart payments and customer tips.

In the DES, arrivals, store and order types, and process times are based on observed probabilities and triangular distributions, while payments and distances are estimated using regression models. These outputs, such as total delivery time, number of batches, item counts, and distances, feed into the SD model, where earnings (Instacart payment and tips) and costs (fuel and depreciation) are calculated. Net earnings are then computed as total earnings minus total costs, with model structures and results presented in the corresponding figures and tables.

3.4.1 Discrete Event Simulation Model

We have developed a DES model with Anylogic using the process modeling library. To better understand the model structure and its processes, the model developed with Anylogic is illustrated in Figure 4. Our discrete-event simulation model is divided into two parts: shopping and delivery.

For the first part, we have determined three store types: Store A has shelf information, Store B has aisle information, Store C provides a more general description of products' location. Moreover, Store B's size is almost half of Store A and C. An Instacart delivery shopper has different shopping speeds per item for each store type. We have used a triangular distribution to enter the shopping speed for each store type. The triangular distribution is a good fit when small data is available, and it takes on skewed forms. We have entered the delivery shopper's minimum, maximum, and mode values of shopping speed that were computed using the data we have. We have computed the probabilities of shopping at each store type using the data we had. Based on the dataset, the probability of shopping at Store A with shelf info for the Instacart delivery shopper is .67, while it is .194 for Store B and .136 for Store C.

For the second part of the DES model, we have built three order types as Instacart batches are comprised of either a single or a combination of two or three orders. After checking out from the store, the Instacart delivery shopper starts delivering groceries based on the order type. Based on the dataset, the probability of delivering a single order is .596, while it is .327 for the combination of two orders and .077 for three orders.

The DES model provides data for time spent at each store type and order type, enabling the comparison of store types and order types. Using the time spent on each order type, we have computed the delivery distance for each order type in a single batch. We have used the computed delivery distance for each batch to calculate fuel consumption cost and vehicle depreciation cost. We have also utilized computed delivery distance to compute Instacart payment for each batch.

Table 4 Multiple Linear Regression Results

Panel A. Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.599[a]	.359	.333	4.09798

a. Predictors: (Constant), Distance, Items

Panel B. ANOVA

Model	Source	Sum of Squares	df	Mean Square	F	Sig.
1	Regression	460.322	2	230.161	13.705	.000[b]
	Residual	822.878	49	16.793		
	Total	1283.200	51			

a. Dependent Variable: InstacartPay

b. Predictors: (Constant), Distance, Items

Panel C. Coefficients

Model	Predictor	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	6.764	1.664		4.066	.000		
	Items	.139	.039	.412	3.554	.001	.974	1.027
	Distance	.413	.094	.507	4.371	.000	.974	1.027

a. Dependent Variable: InstacartPay

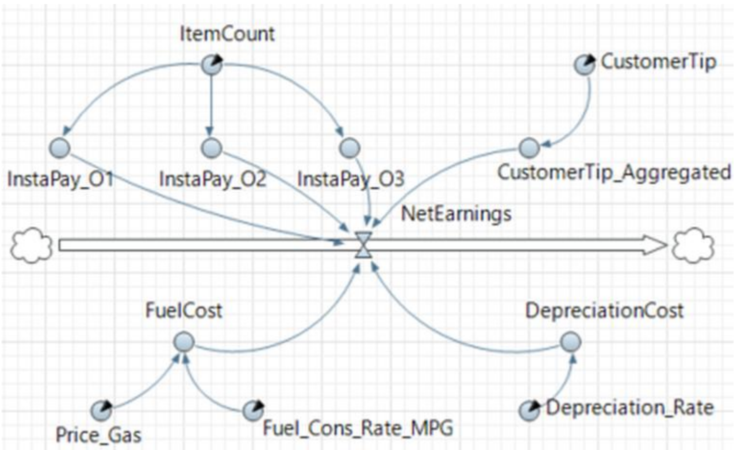

Figure 5 Instacart Delivery Shopper's Net Earnings SD Model

The DES model provides data for time spent at each store type and order type, enabling the comparison of store types and order types. Using the time spent on each order type, we have computed the delivery distance for each order type in a single batch. We have used the computed delivery distance for each batch to calculate fuel consumption cost and vehicle depreciation cost. We have also utilized computed delivery distance to compute Instacart payment for each batch.

Instacart calculates payments for delivery shoppers based on the number of items and size of items in the order, estimated delivery distance, and time of day when the order is placed (Instacart.com, 2021). We have conducted a multiple linear regression model to predict Instacart payment using the number of items and delivery distance as input variables in our dataset (Table 4).

The regression model has an R2 value of .359, explaining almost 36% of the variation in Instacart payment. The adjusted R2 value provides a more accurate prediction than R2, and the model has an adjusted R2 value of .333, which can be interpreted as having a moderate effect. The model is statistically significant with a big F value of 13.705 and a small p-value of .000. Both input variables (number of items and distance) are also statistically significant with p values smaller than .05. Based on the coefficients table, the largest variance inflation factor (VIF) 1.027 is smaller than 10 and the smallest tolerance statistic .974 is greater than 0.10, providing evidence of noncollinearity.

The regression model employed to estimate Instacart payments accounts for only a modest fraction of variance observed in the actual payments ($R^2 \approx 0.36$). This suggests that a considerable fraction of variance still needs to be accounted for, but the regression model can be used as an approximation within the simulation framework.

This amount of explanatory power can be justified by the fact that compensation systems on platform-based websites often involve multiple other dimensions such as varying levels of demand, varying payment schedules based

Table 5 Experiments

#	Parameters			Net Earnings
	Customer Tip	Price of Gas	Fuel Consumption Rate	
1	0	2.8	20	4331.05
2	3	2.8	20	5831.05
3	3	2.0	25	6831.05
4	5	2.0	30	7133.62
5	5	1.5	30	7202.39
6	5	1.5	35	7231.86
7	7	2	45	8225.31
8	10	2.5	40	9650.81
9	10	1.5	20	9599.24

Table 6 Results of 60 Replications

Customer Tip	Price of Gas	Fuel Cons. Rate	Depreciation Rate	n	Mean	SD	Min	Max	CL 95%
0	2.8	20	0.055	20	4281.92	12.60	4260.97	4310.15	5.90
3	2.5	35	0.045	20	6101.09	12.92	6088.23	6133.53	6.05
6	2.2	40	0.035	20	7710.22	20.02	7684.68	7756.25	9.37

on the time and demand, specific time of delivery, etc. Thus, the results of the simulation will have a descriptive nature, showing sensitivity to changes in the parameters and their general behavior.

3.4.2 System Dynamics Simulation Model

We have linked the DES model with the SD model to determine the net earnings of the Instacart delivery shopper using Anylogic. To better understand the model structure and its flows, the model developed with Anylogic is illustrated in Figure 5.

The SD model simulates gross income by summing the earnings from customers and Instacart based on order type. The model computes Instacart payments using the regression equation function we have obtained by regressing the predictor variables of the number of items and total delivery distance against the predicted variable of Instacart payment in our dataset. In this model, item count refers to the value of the parameter number of items we have used for the DES model. The model calculates the aggregated earnings from customer tips by multiplying the number of batches that were produced by the DES with the fixed value assigned to the customer tip parameter.

As for the Instacart delivery shopper's expenses, we have simulated fuel consumption and vehicle depreciation costs. The model calculates fuel cost by multiplying the fixed values assigned to the parameters of gas price and fuel consumption rate with the delivery distance that was found by the regression equation using the total delivery time. Similarly, vehicle depreciation cost is calculated by multiplying the fixed value assigned to the parameter of depreciation rate with the total delivery distance. The DES model provides the total delivery time to compute the total delivery distance.

After obtaining the total earnings and costs, the simulation model calculates the net earnings for the Instacart delivery shopper for the assigned number of batches. Net earnings with the total time measured by the DES model enable us to obtain the hourly income for the Instacart delivery shopper.

3.4.3 Experimental Designs

The experimental design consists of using various values of some of the input variables to study their individual and interaction effects on the outcome. In this paper, we have examined the effects of three parameters on the hourly earnings of an Instacart delivery shopper. We have employed compare runs feature of Anylogic to execute the following nine experiments (Table 5).

3.5 Model Transparency and Replicability

In order to increase clarity and make the model replicable, we describe the key components, assumptions, and functional relationships involved in the simulation model. The discrete event part simulates the workflow of an Instacart shopper that involves a sequence of batch arrival, store selection, shopping process, and delivery process. Each of these components is parameterized using empirically determined distributions from the dataset, such as the triangular distributions for shopping and delivery durations and probability distributions for store type and order type.

The system dynamics part calculates the net profit as the difference between the revenue and the cost components. In turn, revenue comes from Instacart payment and the tips provided by customers. Costs encompass fuel consumption and vehicle depreciation. Instacart payment is predicted using a multiple linear regression model based on the delivery distance and the number of items in delivery. Cost components are computed using the total delivery distance and cost parameters.

The parameters of the model, such as distributions, regression coefficients, and cost rates, are estimated based on the given data set. While AnyLogic was used to implement the model, its structure is quite general and replicable in other software.

4. RESULTS

4.1 Simulation Results

We ran the simulation model sixty times to obtain the net earnings of an Instacart delivery shopper. Table 6 presents the parameter values for each replication and the descriptive statistics of the outcomes. In each replication, 500 batches are completed by the Instacart delivery shopper. Total simulation time for each replication is measured by the time-measure-end feature of Anylogic. Based on that measure, it takes about 416.5 real hours to complete 500 batches.

Table 7 Store Differences

Aspect	Store A	Store B	Store C
Shopping Time (Mean)	~6 minutes longer than Store B	**Shortest** (baseline)	**Longest** (12 min > Store B)
Time Difference vs. Store B	+6 minutes	–	+12 minutes
Batch Selection Frequency	**Highest**	**Lowest**	Moderate
Earnings Optimization Tip	Longer time, more frequent use	**Faster shopping, better for more batches**	Longer time, less selected

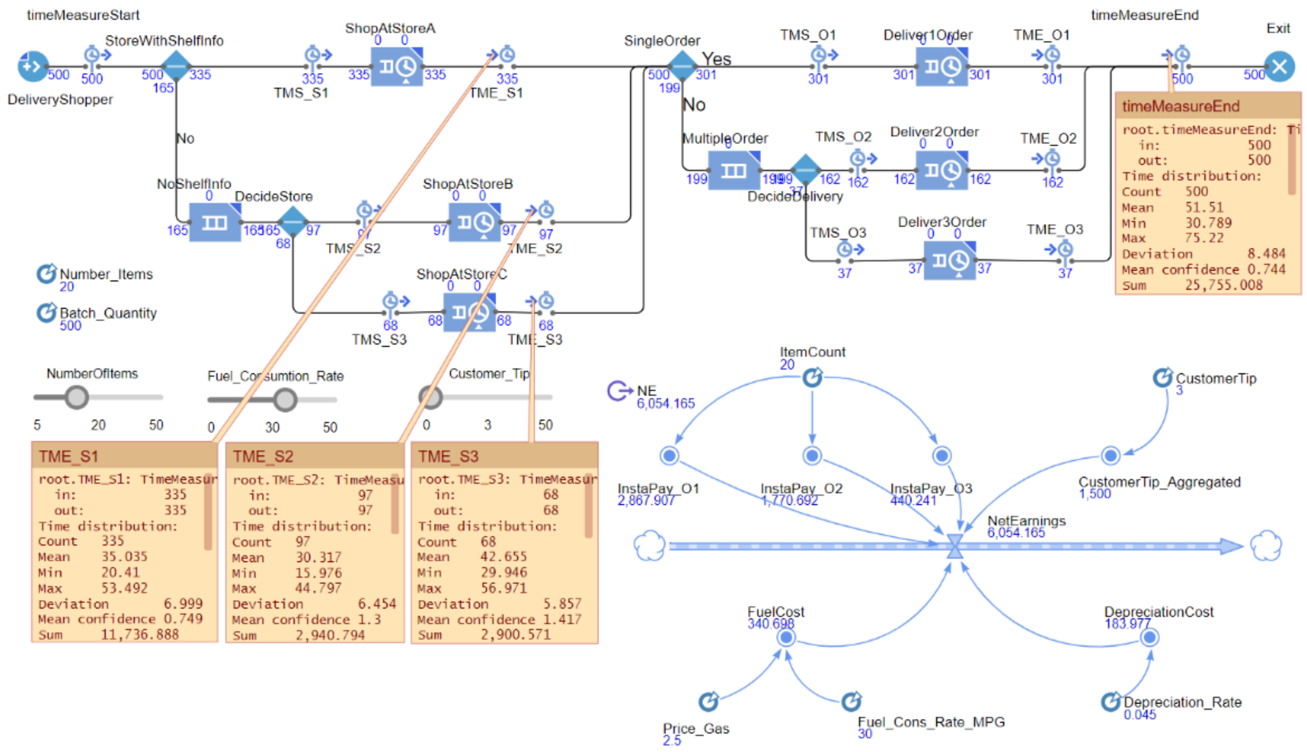

Figure 6 Run Time Capture with Average Values

The first 20 replications represent the worst-case scenario for an Instacart delivery shopper. This scenario does not contain customer tips, and an Instacart delivery shopper makes approximately \$10.27 per hour without any tip. The second 20 replications provide information for the average case scenario. In this scenario, the Instacart delivery shopper's hourly wage becomes \$14.64. The last 20 replications represent the best-case scenario, and the Instacart delivery shopper has hourly earnings of approximately \$18.50.

We have also captured a run-time window of the Anylogic model with average values used for the mentioned parameters to compare the store types. Based on the results, shopping time in Store C is the longest, and Store B is the shortest. There is a six minutes difference between shopping at Store B and Store A, while the difference is 12 minutes between Store B and Store C. While shopping in Store A lasts longer than in Store B, the ratio of selecting a batch from Store A is much higher compared to Store B. An Instacart delivery shopper can enhance earnings by selecting more batches from Store B. In other words, an Instacart delivery shopper may benefit most by selecting more frequent, quicker batches from Store B, even though it's selected less often, it offers time-saving potential, boosting overall earnings efficiency (Figure 6 and Table 7).

4.2 *Verification and Validation*

We have utilized several techniques, including unit checking, face validity, and event validity, to check for validation and verification of the simulation models. We have performed unit checking of the models using the Anylogic unit checking feature, and we have not encountered any unit inconsistencies.

As for face validity, we have consulted the three Instacart delivery shoppers' opinions on the model's logic, structure, and mathematical computations. They have confirmed that our multi-method model is an accurate representation of the actual Instacart delivery shopping processes.

As for event validity and verification, we have entered various input combinations of the three parameters (customer tip, price of gas, fuel consumption rate) we used in our model by using the compare-runs feature of Anylogic software. Based on the results of the compare-runs analysis, the multi-method simulation model appears to accurately represent the specifications of our conceptual model.

Furthermore, to verify our simulation model, we compared our intermediate results with data reported by others. Since our data provided net earnings, we added the

Table 8 Compare Runs Results

#	Parameters			Net Earnings
	Customer Tip	Price of Gas	Fuel Consumption Rate	
1	0	2.8	20	4331.05
2	3	2.8	20	5831.05
3	3	2.0	25	6831.05
4	5	2.0	30	7133.62
5	5	1.5	30	7202.39
6	5	1.5	35	7231.86
7	7	2	45	8225.31
8	10	2.5	40	9650.81
9	10	1.5	20	9599.24

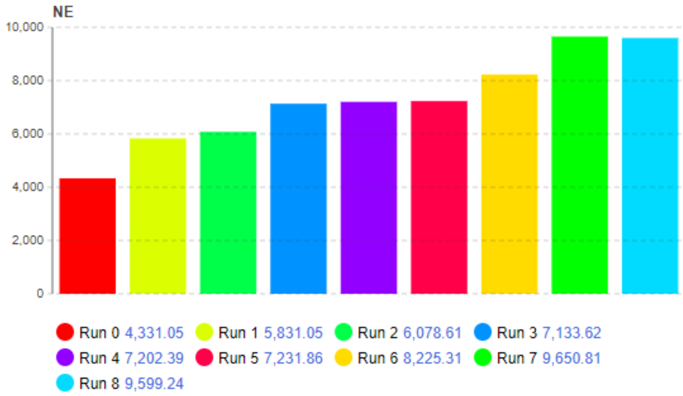

Figure 7 Compare Runs Results

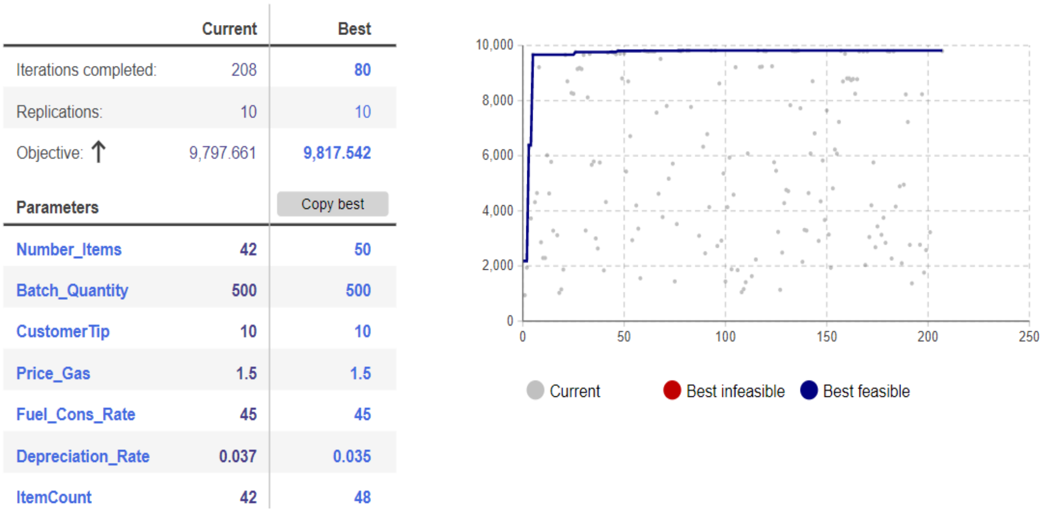

Figure 8 Optimization Progression

costs to estimate gross hourly earnings. The results were similar to those reported by others (Indeed and Gridwise). Therefore, the compare-runs analysis verified the implementation and outcomes of our simulation model (Table 8 and Figure 7).

4.3 Optimization Experiment

We have also conducted an optimization experiment to reveal the best feasible net earnings for the Instacart delivery shopper using the settings from compare runs experiments. Based on the optimization experiment, the Instacart delivery shopper can make approximately \$23.45 per hour in an optimum situation where the customer tip is \$10.00, the price of gas is \$1.5, the fuel consumption rate is 45 miles per gallon, and the depreciation rate is 0.035 (Figure 8).

5. DISCUSSION

Our multi-method simulation model provides a story for our agent, Instacart delivery shopper, to maximize net earnings. A DES model linked to a SD model measures the effects of cost drivers, which are mostly ignored by Instacart delivery shoppers, such as fuel cost and depreciation of the transportation means in use. We find that the income of an Instacart shopper is highly sensitive against the cost of drivers. Therefore, to maximize net earnings, our agent is recommended to drive a vehicle that consumes less gas per mile and loses its value with a low depreciation rate.

Based on the results, shopping time in Store C is the longest and Store B is the shortest. There is six minutes difference between shopping at Store B and Store A, while the difference is 12 minutes between Store B and Store C.

While shopping in Store A lasts longer than in Store B, the ratio of selecting a batch from Store A is much higher compared to Store B. An Instacart delivery shopper can enhance earnings by selecting more batches from Store B.

Whereas it is obvious from the simulation results how important factors like cost drivers, including fuel cost and depreciation, are, there is much more to understand regarding the relationship between batch size, the time spent on serving customers, and stable earnings. Batches of Instacart can be of different sizes: single-order or multi-order (consisting of two or three orders), each of which influences revenue and time differently.

It should be mentioned that multi-order batches produce larger gross earnings per trip since several clients pay at once; however, the service time becomes longer, leading to extra costs of the process and affecting the number of batches completed in a certain period of time. As we see from the simulation, the number of batches declines proportionally to the service time, meaning that although the revenue is bigger, the time efficiency falls. On the other hand, single-order batches do not generate much revenue but are served faster, thus increasing earnings per minute.

The time trade-off is accentuated even further by the individual characteristics of stores. As can be seen from the results, Store B provides the quickest possible shopping for Instacart delivery shoppers, while the times in Store A and Store C become increasingly longer. In spite of Store A being a more popular choice inside the system, the fact that it takes longer for a batch to be processed than in Store B is indicative of structural inefficiencies from the worker's point of view. Shorter batches allow increasing the output rate and minimizing the cost risks related to fuel use and vehicle depreciation, while longer ones mean increased time investment and increased cost sensitivity. Thus, the Instacart delivery shopper faces a decision of trade-off between opting for more frequent but longer batches or targeting shorter, yet possibly scarcer ones.

Apart from time efficiency trade-offs, it should be noted that the simulation results show significant variability in earnings per hour across different scenarios. On average, an Instacart delivery shopper can earn anywhere from roughly \$10.27 to almost \$18.50 an hour, depending on luck with customer tips, the cost of gasoline, and the efficiency of his or her vehicle. Therefore, it follows that higher expected earnings will be correlated with greater variability, creating a dilemma between income maximization and income stability.

In summary, the empirical evidence presented in this study indicates that the best choice behavior for Instacart delivery shoppers does not depend exclusively on the maximization of earnings per batch, but also on the consideration of batch size, trip duration, and risk exposure to cost variance. This shows how important throughput efficiency and risk factors are in deciding how workers should act in platform-based last-mile delivery systems.

This study provides a theoretical contribution by presenting a model to determine how/whether P2P online grocery delivery shopping jobs improve minimum wage worker income and how store and order types of influence Instacart delivery shopper's earnings. From the EUT perspective, it operationalizes hidden factors and makes the worker’s selection more realistic. It also expands the DJT in this context by quantifying the mismatches between reward and effort after the hidden costs. It presents several practical contributions by revealing the net earnings of Instacart delivery shoppers in the Dallas area. This information may guide Instacart delivery shoppers on whether to continue Instacart shopping as a primary or secondary job or quit shopping for Instacart at all. It also demonstrates the best mixture of store and order types as well as vehicle features to maximize net earnings.

The study also provides insights for policymakers to start regulating P2P asset-sharing companies based on minimum wage standards. Furthermore, it may lead Instacart to offer more information on product locations in every store to decrease shopping time. Lastly, transparency regarding actual earnings may present incentives to platforms like Instacart to review their payment strategies.

The results should be considered in light of model uncertainty, especially considering that the model for payment estimation does not account for all sources of variance in platform payouts. Although the simulation shows general patterns and sensitivities, real earnings can vary owing to unknown platform behavior.

The regression model employed to estimate Instacart payments accounts for only a modest fraction of variance observed in the actual payments ($R^2 \approx 0.36$). As Ozili (2023) notes, R^2 values of this magnitude are common and acceptable in empirical social science research, particularly when the model includes statistically significant predictors. While a considerable portion of the variance in our dataset remains unexplained, the regression model nevertheless serves as a reasonable approximation of Instacart payments within our simulation framework.

The Instacart payment equation is built directly into the SD model, so any unexplained variation in the regression carries through to the simulated earnings. To account for this, we ran 60 simulations across worst-, average-, and best-case scenarios and report a range of outcomes rather than a single estimate. The hourly earnings of \$10.27, \$14.64, and \$18.50 should therefore be interpreted as a realistic range that reflects both parameter variation and model uncertainty. This aligns with the purpose of the simulation, which is to highlight general patterns and sensitivities rather than provide precise predictions of absolute earnings.

This level of explanatory power reflects the nature of platform-based compensation systems, where payments depend on many factors such as demand fluctuations, timing, and other platform-specific adjustments. As a result, the simulation results should be interpreted as descriptive, highlighting general patterns and sensitivity to key parameters rather than precise predictions.

6. CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

In this paper, we have investigated whether P2P businesses help the minimum wage standards in the context of Instacart. Based on the different scenarios employed in our simulation, we conclude that both the customer tips and the cost drivers of Instacart shoppers have a significant impact on earnings. Only the best-case scenario, in which the customer tips are set to \$6 on average, fuel cost is set to \$2.2 per gallon, and a vehicle of which the consumption rate is set to 40 miles per gallon, yields an hourly wage of $18.50. The viability of Instacart workers achieving a stable income passing the minimum wage is highly dependent on external factors. The cost drivers can dramatically reduce the net income, although gross income can be attractive upfront.

As for the limitations and future research, first, we acknowledge that our empirical foundation is based on data from a single Instacart shopper operating in the Dallas area, which limits the external validity and representativeness of the absolute earnings estimates reported here. Second, the same methodology could be used in only specific shops to lay out how attractive they are in terms of physical shopping experiences and to compare their efficiency from the perspective of online grocery shoppers. Third, future research may examine the effects of vehicle maintenance and insurance as well as random traffic violation tickets that may occur and opportunity cost as additional cost drivers. Fourth, sometimes customers tip Instacart delivery shoppers in cash during the delivery of groceries in addition to their tips on the Instacart app to show satisfaction of service. Future research may also consider adding cash tips as an input variable occurring randomly in the model. Fifth, an agent-based model can be used to simulate Instacart delivery shopping. Lastly, future studies can also consider the potential differences between male and female workers and different ethnicities as factors impacting the preferences of the workers.

REFERENCES

Adams, J. S. (1965). Inequity in social exchange. In L. Berkowitz (Ed.), *In Advances in experimental social psychology* (Vol. 2, pp. 267–299). Academic Press.

Agatz, N., Mes, M., & Schmidt, M. (2025). Innovations, technologies, and the economics of last-mile operations: A call for research in operations management. *Journal of Operations Management, 71*(2), 166–175.

Al Mashalah, H., Hassini, E., & Mishra, D. (2025). How do disruptions and last-mile delivery logistics affect shopping behaviour? *Operations and Supply Chain Management: An International Journal, 18*(4), 600–616. https://doi.org/10.31387/oscm0630494

Arevalo-Ascanio, R., De Meyer, A., Gevaers, R., Guisson, R., & Dewulf, W. (2024). Location-routing problem for integrated supply chain network design with first and last mile: A critical literature review. *Operations and Supply Chain Management: An International Journal, 17*(2), 206–219. https://doi.org/10.31387/oscm0570423

Baalsrud Hauge, J., & Jeong, Y. (2024). From novice to expert: advancing step-by-step simulation guideline for urban logistics with an open-source simulation tool. *The International Journal of Logistics Management, 35*(5), 1417–1433.

Bardhi, Fluera, and Giana M. Eckhardt (2012). Access-based consumption: The case of car sharing, *Journal of Consumer Research, 39* (4), 881–898.

Bardhi, Fluera, and Giana M. Eckhardt (2017). Liquid consumption, *Journal of Consumer Research, 44* (3), 582–597.

Benjaafar, S., & Hu, M. (2020). Operations management in the age of the sharing economy: What is old and what is new? *Manufacturing and Service Operations Management, 22*(1), 93–101. https://doi.org/10.1287/msom.2019.0803

Benoit, S., Baker, T. L., Bolton, R. N., Gruber, T., & Kandampully, J. (2017). A triadic framework for collaborative consumption: Motives, activities and resources & capabilities of actors. *Journal of Business Research, 79*, 219–227.

Berg, J. (2015). Income security in the on-demand economy: Findings and policy lessons from a survey of crowdworkers. *Comparative Labor Law & Policy Journal*, *37*, 543.

Boyer, K. K., & Hult, G. T. M. (2005). Extending the supply chain: Integrating operations and marketing in the online grocery industry. *Journal of Operations Management, 23*(6), 642–661.

Caldieraro, F., Zhang, J. Z., Cunha, M., Jr., & Shulman, J. D. (2018). Strategic information transmission in peer-to-peer lending markets. *Journal of Marketing, 82*(2), 42–63.

Caliskan, F., Idug, Y., Gligor, D., & Hong, S. J. (2025). Blockchain technology for building buyer-supplier trust and transparency in supply chains: An experimental study on P2P online marketplace vendors. *Industrial Marketing Management, 124*, 239–253.

Castillo, V. E., Bell, J. E., Rose, W. J., & Rodrigues, A. M. (2022). Designing technology for on-demand delivery: The effect of customer tipping on crowdsourced driver behavior and last mile performance. *Journal of Operations Management, 68*(5), 424–453.

Chaudhari, S. L., & Sinha, M. (2021). A study on emerging trends in Indian startup ecosystem: big data, crowd funding, shared economy. *International Journal of Innovation Science.*

Cohen, M. C., Fiszer, M. D., & Kim, B. J. (2022). Frustration-based promotions: Field experiments in ridesharing. *Management Science, 68*(4), 2432-2464.

Colquitt, J. A., Conlon, D. E., Wesson, M. J., Porter, C. O., & Ng, K. Y. (2001). Justice at the millennium: a meta-analytic review of 25 years of organizational justice research. *Journal of Applied Psychology, 86*(3), 425.

de Moraes Ramos, G., Daamen, W., & Hoogendoorn, S. (2011). Expected utility theory, prospect theory, and regret theory compared for prediction of route choice behavior. *Transportation Research Record, 2230*(1), 19–28.

Eckhardt, G. M., Houston, M. B., Jiang, B., Lamberton, C., Rindfleisch, A., & Zervas, G. (2019). Marketing in the sharing economy. *Journal of Marketing, 83*(5), 5–27.

Einav, L., Farronato, C., & Levin, J. (2016). Peer-to-peer markets. *Annual Review of Economics, 8*, 615–635.

Ertz, M., Durif, F., & Arcand, M. (2019). A conceptual perspective on collaborative consumption. *AMS Review, 9*(1), 27–41.

Ewedairo, K., Chhetri, P., Dodson, J., & Shee, H. (2024). Developing a strategic framework to build future last mile delivery scenarios: A scenario thinking approach. *Operations and Supply Chain Management: An International Journal, 17*(1), 32–49. https://doi.org/10.31387/oscm056 0412

Festinger, L. (1957). *A theory of cognitive dissonance*. Stanford University Press.

Fishburn, P. C. (1991). Nontransitive preferences in decision theory. *Journal of Risk and Uncertainty, 4*(2),113–134.Frenken,

Koen, and Juliet Schor (2017). Putting the sharing economy into perspective. *Environmental Innovation and Societal Transitions, 23* (June), 3–10.

Frenken, K., & Schor, J. (2017). Putting the sharing economy into perspective. *Environmental Innovation and Societal Transitions, 23*, 3–10.

Gobble, M. M. (2017). Defining the sharing economy. *Research Technology Management, 60* (2). 59–61.

Greenberg, J. (1990). Organizational justice: Yesterday, today, and tomorrow. *Journal of Management, 16*(2), 399–432.

Gridwise. (2021). How much do Instacart shoppers make? Retrieved April 14, 2021, from https://gridwise.io/how-much-do-instacart-shoppers-make

Hamari, J., Sjöklint, M., & Ukkonen, A. (2016). The sharing economy: Why people participate in collaborative consumption. *Journal of the Association for Information Science and Technology, 67*(9), 2047–2059.

Hu, M., & Zhou, Y. (2018). *Dynamic type matching*. ArXiv.https://doi.org/10.2139/ssrn.2592622

Huynh, T., & Gurtner, S. (2023). Resistance to the sharing economy: Why some consumers and providers do not participate in P2P sharing. *Journal of Cleaner Production, 422*, 138628.

Idug, Y., Niranjan, S., Manuj, I., Gligor, D., & Ogden, J. (2023). Do ride-hailing drivers' psychological behaviors influence operational performance? *International Journal of Operations & Production Management, 43*(12), 2055–2079.

Idug, Y., Gligor, D., Porchia, J., Niranjan, S., Manuj, I., & Nowicki, D. R. (2024). Exploring the impact of rider–driver ethnicity match/mismatch in ride-hailing. *International Journal of Physical Distribution & Logistics Management, 54*(3), 301–329.

Indeed. (2021). *Average Instacart shoppers personal shopper salary*. Retrieved April 14, 2021, from https://www.indeed.com/cmp/Instacart-Shoppers/salaries/PersonalShopper

Instacart Official Website. Retrieved March 2, 2021, from https://www.instacart.com/

Ivanov, D. (2019). Disruption tails and revival policies: A simulation analysis of supply chain design and production-ordering systems in the recovery and post-disruption periods. *Computers & Industrial Engineering, 127*, 558–570.

Jiang, A., Yuan, H., & Li, D. (2021). A two-stage optimization approach on the decisions for prosumers and consumers within a community in the Peer-to-peer energy sharing trading. *International Journal of Electrical Power & Energy Systems, 125*, 106527.

Kenney, M., & Zysman, J. (2016). The rise of the platform economy. *Issues in Science and Technology, 32*(3), 61.

Klein, J. F., Merfeld, K., Wilhelms, M. P., Falk, T., & Henkel, S. (2022). Buying to share: How prosumption promotes purchases in peer-to-peer asset sharing. *Journal of Business Research, 143*, 171–183.

Lessig, L. (2008). *Remix: Making art and commerce thrive in the hybrid economy*. Penguin Press.

Lobel, O. (2017). The gig economy & the future of employment and labor law. *University of San Francisco Law Review, 51*(1), 51–74.

Morgan, J. S., Howick, S., & Belton, V. (2017). A toolkit of designs for mixing discrete event simulation and system dynamics. *European Journal of Operational Research, 257*(3), 907–918.

Münzel, A., Pera, R., Spangenberg, J., & Zizzo, D. (2019). The emotional path to sustainability: Emotional brand attachment and peer-to-peer car sharing. *Journal of Cleaner Production, 241*, 118502.

Münzel, K., Piscicelli, L., Boon, W., & Frenken, K. (2019). Different business models–different users? Uncovering the motives and characteristics of business-to-consumer and peer-to-peer carsharing adopters in The Netherlands. *Transportation Research Part D: Transport and Environment, 73*, 276–306.

Oliveira, J. B., Jin, M., Lima, R. S., Kobza, J. E., & Montevechi, J. A. B. (2019). The role of simulation and optimization methods in supply chain risk management: Performance and review standpoints. *Simulation Modelling Practice and Theory, 92*, 17–44.

Ozili, P. K. (2023). The acceptable R-square in empirical modelling for social science research. In Social research methodology and publishing results: A guide to non-native English speakers (pp. 134–143). *IGI Global Scientific Publishing.*

Ozkan E, & Ward, A. (2019). Dynamic matching for real-time ridesharing. *Stochastic Systems 10*(1), 29–70.

Park, K. H., Pan, X., & Dresner, M. E. (2025). Targeting online sales through last-mile delivery platform integration. *Journal of Operations Management, 71*(2), 195–219.

Penazzi, S., Accorsi, R., Ferrari, E., Manzini, R., & Dunstall, S. (2017). Design and control of food job-shop processing systems: A simulation analysis in the catering industry. *The International Journal of Logistics Management, 28*(3), 782–797.

Philip, H. E., Ozanne, L. K., & Ballantine, P. W. (2015). Examining temporary disposition and acquisition in peer-to-peer renting. *Journal of Marketing Management, 31*(11-12), 1310–1332.

Pujawan, N., Arief, M. M., Tjahjono, B., & Kritchanchai, D. (2015). An integrated shipment planning and storage capacity decision under uncertainty: A simulation study. *International Journal of Physical Distribution & Logistics Management, 45*(9/10), 913–937.

Puram, P., Gurumurthy, A., Narmetta, M., & Mor, R. S. (2022). Last-mile challenges in on-demand food delivery during COVID-19: understanding the riders' perspective using a grounded theory approach. *The International Journal of Logistics Management, 33*(3), 901–925.

Puschmann, T., & Alt, R. (2016). Sharing economy. *Business Information Systems Engineering, 58*(1), 93–99.

Rosenblat, A., & Stark, L. (2016). Algorithmic labor and information asymmetries: A case study of Uber's drivers. *International Journal of Communication, 10*, 27.

Rupp, D. E., Shapiro, D. L., Folger, R., Skarlicki, D. P., & Shao, R. (2017). A critical analysis of the conceptualization and measurement of organizational justice: Is it time for reassessment? *Academy of Management Annals, 11*(2), 919–959.

Savelsbergh, Martin WP, and Marlin W. Ulmer. "Challenges and opportunities in crowdsourced delivery planning and operations." 4OR 20.1 (2022): 1–21.

Shao, Z., Zhang, L., Li, X., & Zhang, R. (2022). Understanding the role of justice perceptions in promoting trust and behavioral intention towards ridesharing. *Electronic Commerce Research and Applications, 51*, 101119.

Simchi-Levi, D., Wang, H., & Wei, Y. (2018). Increasing supply chain robustness through process flexibility and inventory. *Production and Operations Management, 27*(8), 1476–1491.

Sorvino, C. (2021). *Instacart survived Covid chaos — But can it keep delivering after the pandemic?* Forbes. from https://www.forbes.com/sites/chloesorvino/2021/01/27/instacart-survived-covid-chaos---but-can-it-keep-delivering-after-the-pandemic/

Statista. (2021). Grocery delivery app download growth due to coronavirus (COVID-19) pandemic in the United States as of March 2020. Retrieved March 2, 2021, from https://www.statista.com/statistics/1104519/grocery-delivery-app-growth-coronavirus-us/

Sundararajan, A. (2017). *The sharing economy: The end of employment and the rise of crowd-based capitalism*. MIT press.

Tako, A. A., & Robinson, S. (2012). The application of discrete event simulation and system dynamics in the logistics and supply chain context. *Decision Support Systems, 52*(4), 802–815.

Ulmer, M. W., & Savelsbergh, M. (2020). Workforce scheduling in the era of crowdsourced delivery. *Transportation Science, 54*(4), 1113–1133.

von Neumann, J., & Morgenstern, O. (1944). *Theory of games and economic behavior*. Princeton University Press.

Weber, T. A. (2016). Product pricing in a peer-to-peer economy. *Journal of Management Information Systems, 33*(2), 573–596.

Wilhelms, M. P., Merfeld, K., & Henkel, S. (2017). Yours, mine, and ours: A user-centric analysis of opportunities and challenges in peer-to-peer asset sharing. *Business Horizons, 60*(6), 771–781.

Wilhelms, M. P., Henkel, S., Falk, T., (2017). To earn is not enough: A means-end analysis to uncover peer-providers' participation motives in peer-to-peer carsharing. *Technological Forecasting and Social Change, Elsevier, 125*, 38–47.

Wirtz, J., So, K. K. F., Mody, M. A., Liu, S. Q., & Chun, H. E. H. (2019). Platforms in the peer-to-peer sharing economy. *Journal of Service Management, 30*(4), 452–483.

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