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Analysis of the Impact of Stakeholders on Companies with Home Delivery Platforms Using Hybrid Optimization and Simulation Approaches

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Abstract

Logistics companies have developed virtual platforms where users get food and medicine via the different businesses associated with these applications. The efficient delivery of these products through these platforms is defined as the Meal Delivery Routing Problem (MDRP). These platforms are the subject of legal and regulatory research due to their collaborative economy model. These platforms function only as service promoters, whereby there should be no labor relations involving businesses or domiciliary workers. These characteristics dilute and alter the employment relationships between worker and employer, decreasing a worker's labor rights, well-being or health, and compensation. This research proposes a simulation model with interchangeable policies and uses behavioral data on domiciliary workers to analyze their multidimensional impact on stakeholders (ordering platforms, businesses, users, and domiciliary workers). The proposed methodology has been applied in a real company, demonstrating its efficiency, improving domiciliary workers' conditions, and decreasing potential losses.

Keywords: Domiciliary workers; meal delivery routing problem; on demand; discrete event simulation; stakeholders.

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1. Introduction

Evolving technologies and communications have affected logistics, especially in the transport sector, specifically in last-mile logistics, where people and most businesses interact. This activity is carried out in the last part of the supply chain to meet the final customer's needs. Today, there are companies specializing in these activities, that is, companies that meet people's daily needs by delivering groceries or restaurant takeout, providing certain services, taking a pet for a walk, and providing door-to-door transportation, among others. How these on-demand companies work is through a commercial digital platform; a web page or mobile application is connected to different warehouses or companies offering goods, and at the same time, the system allows these goods to be bought by users (Berg *et al*., 2018). These platforms have a group of domiciliary workers who are responsible for picking up an order at an establishment and then transporting it to the place where the corresponding user is located to complete the delivery of a good, with some general constraints—for example, the order must be in good condition, the time for delivery must be less than one hour, and the deliverer must pay sufficient attention to the corresponding user.

Studies on this platform must incorporate elements of their current legal status in the countries in which they operate; on-demand logistics services companies take advantage of the legal gaps that exist via these platforms to obtain a net benefit, specifically, not having labor contracts that bind a domiciliary worker. This way, a fleet of domiciliary workers does not have labor guarantees, such as social security affiliation or pension funds, defined schedules, or overtime pay. Companies argue that home users are the customers of their applications and that they are free to provide their services when they want and in the way they want. A sale on these applications promises that it connects people and their needs. However, domiciliary workers argue that these statements are not entirely factual because, in the background of each application, the algorithms that are implemented to connect them are rigorous; they indirectly give orders to the domiciliary workers and penalize them in severe ways if they do not meet specific requirements (Quintero Rojas, 2020). A good argument in favor of the position of the domiciliary worker is the new regulation by the

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European Commission whereby a domiciliary worker must be classified as an employee of a platform, which has been supported in different studies that prove that there is a relationship of subordination between a domiciliary worker and the company. The existence of such subordination means that there is a need for a link, through an employment contract, between the company that administers the application and its domiciliary workers.

In the context of digital home-delivery platforms, the stakeholders perspective is particularly relevant because these firms work as multi-sided ecosystems in which domiciliary workers, restaurants, users, and the platform itself are structurally interdependent. Recent research on platform-based business models highlights that algorithmic decisions directly shape the economic outcomes, working conditions, and service quality experienced by each stakeholder group (Kenney & Zysman, 2016; Parker *et al*., 2016). This creates a structural tension between operational efficiency, which platforms pursue through optimization and automation, and stakeholder welfare, particularly for domiciliary workers whose income stability, workload, and exposure to risk are governed by opaque algorithms (De Stefano, 2016; Vallas & Schor, 2020). From a stakeholder theory perspective, prioritizing efficiency at the expense of worker well-being may generate short-term cost advantages but can undermine long-term organizational sustainability by increasing labor turnover, regulatory pressure, and reputational risk. Consequently, analyzing delivery routing and assignment policies through a stakeholder-based lens allows this study to assess not only technical performance but also how operational decisions impact companies' strategic outcomes, legitimacy, and capacity to create shared value across all actors involved in the platform economy.

The gig economy has sparked extensive attention due to persistent concerns about labor precarity, algorithmic management, and inequitable outcomes for workers compared with platform interests. Recent research shows that algorithmic control in app-based gig work enhances operational efficiency but can also diminish worker well-being and performance, revealing inherent power imbalances between platforms and labor (Liu & Yin, 2024; van Doorn, 2024). Systematic reviews of gig work further highlight power asymmetries and limited autonomy among workers, who navigate opaque algorithmic systems that constrain bargaining capacity and reinforce structural inequities (Pilatti *et al*., 2024). These dynamics point to broader patterns of precariousness and wage disparities that affect gig workers globally, underscoring the importance of understanding how platform policies influence economic outcomes across stakeholder groups. Thus, sitting this study within the contemporary gig economy context underscores both the socioeconomic and strategic implications of delivery platform operations on company performance and worker welfare.

Simulation and optimization constitute particularly suitable methodological tools for analyzing on-demand delivery platforms because they allow the representation of complex, dynamic, and multi-actor systems in which operational decisions generate heterogeneous impacts across stakeholders. Optimization models provide a rigorous framework to formalize decision rules, constraints, and goals associated with order assignment and routing, while simulation enables the evaluation of these rules under realistic and uncertain operational conditions. Moreover, the combined use of simulation and optimization offers a flexible analytical environment in which alternative regulatory scenarios and policy interventions can be systematically tested. This capability is especially relevant in the context of gig economy, where public authorities may introduce diverse regulatory mechanisms—such as minimum income guarantees, workload limits, or fairness-oriented allocation rules—whose effects cannot be directly observed in real systems without significant social and economic risks. Therefore, hybrid simulation-optimization approaches not only support operational decision-making but also provide a robust framework for exploring the potential consequences of public policies and governance strategies on platform performance and stakeholder welfare.

The proposed model also analyzes the different elements of the operation of an ordering platform to identify the possible actions that could improve the well-being of the stakeholders (businesses, users, domiciliary workers, and platform). Specifically, the proposed model incorporates four optimization and order allocation models and, using behavioral data on domiciliary workers, allows an analysis of the impact of the level of sharing economy that directly affects all stakeholders in the platform. These policies affect the ordering platform economically, maximizing the profits of an application, the most significant number of orders placed must be fulfilled, and domiciliary workers must accept their assignments at the lowest cost allowed by the application's auction system. Fulfilling this goal implies directly controlling the actions of domiciliary workers. However, this, in turn, can lead to a decrease in the quality of their services (longer delivery times).

This paper proposes a discrete event simulation model to reveal the internal dynamics of ordering platforms that apply to the working conditions of domiciliary workers and users' consumption habits. Real test data from a Colombian food delivery application have been used to test the efficiency of the proposed methodology. These instances contain real locations of businesses, users, and domiciliary workers. The proposed methodology uses existing simulation models (Reyes *et al*., 2018) to determine the arrival of new users to the focal system, and the results obtained from a survey conducted directly with domiciliary workers under application are used (Valencia Jiménez, 2021) to simulate the actions taken by domiciliary workers while the simulation model progresses through a typical day of operations.

In section 2, a review of the literature related to the dispatch and assignment of orders in online home platforms is carried out. Section 3 describes the research problem. Section 4 describes the proposed methodology in detail. Finally, the computational results and conclusions are detailed in Sections 5 and 6.

2. Literature Review

2.1. Operational Optimization in Digital Delivery Platforms

Digital delivery platforms have attracted significant attention in the operations research and transportation literature, particularly on routing, order assignment, and delivery time minimization. Numerous studies propose optimization-based approaches—such as vehicle routing problems (VRP), dynamic assignment models, and simulation-based heuristics—to improve efficiency under time windows, stochastic demand, and real-time constraints (Boysen *et al*., 2022; Ulmer *et al*., 2020; Reyes *et al*., 2018). These models demonstrate substantial gains in delivery speed and cost reduction, reinforcing the central role of algorithmic decision-making in platform performance.

Ulmer *et al*. (2020) consider a stochastic dynamic pickup and delivery problem where a fleet of drivers delivers food from a set of restaurants to order customers spontaneously. The sources of stochasticity for this problem are twofold: first, customers are unknown until they place an order; second, the time the food is ready at the restaurant is still uncertain. The authors propose a parametrizable cost function approximation (CFA) which improves service significantly for all stakeholders compared to the current practice of a real company.

However, this body of literature largely prioritizes operational efficiency from a system-centric perspective, treating domiciliary workers as homogeneous resources and rarely incorporating labor conditions, income variability, or workload balance into objective functions. While recent contributions have begun to integrate fairness constraints or multi-objective formulations (Martínez-Sykora *et al*., 2024), most approaches are still abstract away from the broader organizational and social implications of routing and assignment policies. As a result, the dominant optimization paradigm remains limited in its capacity to assess how technical efficiency translates into sustainable value creation across multiple stakeholders.

2.2. Platform-Based Business Models and Algorithmic Management

Beyond operational efficiency, digital delivery services work as multi-sided platforms that coordinate interactions among users, restaurants, domiciliary workers, and the platform owner. Research on platform-based business models emphasizes the role of data-driven coordination and network effects in shaping competitive advantage (Parker *et al*., 2016; Kenney & Zysman, 2016). In this context, algorithmic management systems play a critical role by automating task allocation, pricing, performance evaluation, and incentives.

Recent studies highlight that algorithmic management significantly enhances operational scalability and managerial control within digital labor platforms yet worsens structural power asymmetries between platforms and workers (Kadolkar *et al*., 2024; Muldoon &

Raekstad, 2022). In the context of food delivery platforms, routing algorithms and order assignment systems function not merely as technical tools for optimizing logistical efficiency but also as core governance mechanisms that directly shape domiciliary workers' economic outcomes, workload intensity, and access to work opportunities (Huang, 2022). This dual functionality—serving both as operational optimization and organizational control—positions algorithms as central actors in the reconfiguration of workplace authority and employment relations in the gig economy.

Despite this increasingly recognized dual role, a persistent epistemic gap remains between critical studies of platform labor and the technical domains of operations research and algorithm design. Emerging research suggests that hybrid models combining rule-based transparency with adaptive machine learning can support both operational efficiency and worker autonomy, particularly when workers are involved in shaping the parameters and constraints of algorithmic decision-making (Galière, 2020; Öborn *et al.,* 2024). By aligning technical implementation with sociotechnical theory, future developments in platform design can move beyond mere efficiency maximization toward creating sustainable, just, and resilient digital labor ecosystems.

2.3. Gig Economy, Labor Conditions, and Stakeholder Impacts

Studies consistently report that platform workers face limited autonomy and exposure to algorithmic control mechanisms that shape work availability and compensation, focusing on precarity, income volatility, and algorithmic wage determination (Vallas & Schor, 2020; van Doorn, 2024). These conditions are particularly salient in delivery services, where domiciliary workers' earnings depend on opaque allocation rules and dynamic pricing schemes.

The gig economy in Latin America has rapidly expanded over the past decade, driven by digital platform proliferation, economic informality, and shifting labor market dynamics. While platforms such as Rappi, Uber, DiDi, and iFood have created new income opportunities for millions, they have also introduced complex labor challenges characterized by algorithmic management, precarious working conditions, and ambiguous regulatory frameworks. These platforms operate under business models that classify workers as independent contractors rather than formal employees, thereby circumventing traditional labor protections such as minimum wage guarantees, social security contributions, collective bargaining rights, and occupational safety standards (Arriagada *et al.*, 2023; Bensusán & Santos, 2021). This structural arrangement enables cost externalization onto workers, who bear risks related to vehicle maintenance, fuel costs, insurance, and unpredictable earnings.

Stakeholder impacts extend across multiple dimensions, affecting not only workers but also consumers, platform operators, and regulatory institutions. While consumers benefit from convenience and competitive pricing, these advantages are structurally sustained through cost-shifting practices that compromise fair labor standards. Platform companies, driven by scalability and investor returns, leverage algorithmic efficiency to maximize throughput while minimizing direct responsibility for workforce welfare.

2.4. Stakeholder Theory and the Need for an Integrated Perspective

Stakeholder theory provides a valuable framework to integrate these fragmented streams by emphasizing that firm performance depends on the firm's ability to balance the interests of multiple interdependent actors (Freeman *et al*., 2010). Applied to delivery platforms, this perspective suggests that routing and assignment policies influence not only efficiency metrics but also stakeholder welfare, legitimacy, and long-term sustainability. However, existing studies tend to focus either on technical optimization or on social critique, rarely combining both dimensions in a unified analytical framework.

Recent calls in the literature advocate multi-dimensional performance evaluation in platform-based systems, incorporating operational efficiency, worker well-being, and organizational resilience (Jarrahi *et al*., 2020). Nevertheless, empirical and simulation-based models that explicitly quantify trade-offs between efficiency and stakeholder outcomes remain scarce, particularly in the context of real-time delivery operations.

2.5. Research Gap

Despite significant advances in routing optimization, platform governance, and gig economy research, there is a lack of integrative approaches that assess how algorithmic delivery policies simultaneously affect operational performance and stakeholder outcomes. Prior studies either optimize efficiency without accounting for labor impacts or analyze worker conditions without modeling the operational logic of platforms. This gap limits the ability of companies and policymakers to evaluate the strategic consequences of algorithmic decision-making. To address this limitation, this study proposes a hybrid modeling approach that combines optimization and simulation to evaluate delivery assignment policies through a stakeholder-oriented lens, offering insights into both technical performance and organizational sustainability

3. Problem Description

Digital on-demand delivery applications have become a central component of urban service ecosystems in Latin America, facilitating the rapid distribution of goods and services through platform-based coordination mechanisms. These applications work as multi-sided systems that connect provider companies, users, and domiciliary workers through algorithmic decision-making processes responsible for order assignment, routing, and service prioritization. As demand grows and operational environments become increasingly dynamic, platforms face significant challenges in maintaining efficiency while managing the diverse and often conflicting interests of the actors involved.

In this context, order allocation and routing decisions are typically driven by optimization models designed to minimize delivery times and operational costs. While such approaches are effective in improving service responsiveness, they often overlook the implications of these decisions for domiciliary workers' working conditions, including workload distribution, income variability, and time utilization. In Latin America, these issues are worsened by structural labor vulnerabilities, such as informality, limited social protection, and strong competition among workers, which intensify the gap between platforms and domiciliary workers' objectives.

From a stakeholder perspective, prioritizing operational efficiency without considering its effects on domiciliary worker's work quality may compromise long-term platform sustainability, leading to higher turnover, service instability, and increased regulatory pressure. At the same time, provider companies and users depend on reliable delivery performance to keep customer satisfaction and brand value, reinforcing the need for balanced decision-making frameworks. Consequently, there is a need for analytical approaches that explicitly capture the trade-offs between efficiency-driven optimization and stakeholder-related outcomes within on-demand delivery systems.

Based on these considerations, this study seeks to improve the operation of the applications' orders, with a focus on the quality of work for domiciliary workers to benefit all stakeholders in this process through a collaborative work model. To properly understand the event framework generated by our simulation, it is necessary to formalize the development of the optimization model behind the simulation, known in the literature as the MDRP, first described by Reyes *et al.* (2018). This model is part of the set of problems in the dynamic vehicle routing problem (DVRP). In this case, involving the assignment of orders to an on-demand application, the following adaptation of the MDRP model was employed:

Let U be the set of users who want to place orders, with each user $u \in U$ associated with a delivery location l_u. Let R be the set of restaurants where the food must be collected, where each restaurant $r \in R$ has associated with it a location l_r, where the order must be collected. Then, let O be the set of orders made by users, where each of these orders $or \in O$ has a partner: a restaurant $r_0 \in R$ and the user $or \in U$, a preparation time of the order from when α starts or until it is ready e_{or}, an order collection time s^r and a service delivery time s^u tied to the user who placed the order. Let C be the set of domiciliary workers who handle delivering the orders belonging to set O. Thus, domiciliary worker $c_{or} \in C$ will be the domiciliary worker assigned to the order $or \in O$. Each of these domiciliary workers has their vehicle (car, motorcycle, or bicycle) and may or may not be assigned to an order. The domiciliary worker $c \in C$ is associated with a time in which the system enters the line c, a location l_c, and a disconnection time of the system d_c, $d_c > e_c$. At the end of the shift of each domiciliary worker, the obtained earnings are calculated as $\sum_{m=1}^{i} p_i \, \forall \, r \in R$, where p_i is the compensation for each order placed, which is divided into a base amount and a variable amount for each order that depends on the time it takes for an order to be accepted (auction model), and m is the number of orders fulfilled by domiciliary worker $c \in C$. Orders from the same restaurant can be grouped into routes, which have one place for order collection but multiple places for order delivery. Let S be the set of routes, and any route $s \in S$ must meet $|\{r_o, \forall\, o \in S\}| = 1$. The information of a user U associated with an order O is only revealed to the domiciliary worker R at the time agrees to fulfill the order.

Beyond its technical contributions, this study provides relevant insights into the field of management by demonstrating that algorithmic assignment policies can be designed to simultaneously enhance operational efficiency and improve delivery workers' welfare. The results suggest that optimization models are not merely technical tools but strategic instruments that shape organizational outcomes and stakeholder relationships. From a managerial perspective, the findings highlight that platform companies can adopt hybrid assignment policies to balance productivity and labor sustainability, rather than prioritizing efficiency at the expense of workforce stability. Furthermore, the proposed framework offers a basis for evaluating regulatory interventions, showing how alternative policy scenarios may influence platform performance and stakeholder welfare. Thus, the study contributes to the management literature by linking algorithmic design decisions with strategic and regulatory implications for platform-based organizations.

4. Proposed Methodology

The proposed methodology is implemented through a discrete-event simulation framework designed to replicate the dynamic operation of on-demand delivery platforms. The simulation loads real-world instances consisting of geographically referenced orders and available domiciliary workers, represented by latitude-longitude coordinates. During the simulation horizon—defined over full operational days or selected time windows—orders arrive dynamically and are assigned to couriers through a Meal Delivery Routing Problem (MDRP) formulation. Routing decisions are computed using an open-source routing engine (OSRM), which estimates travel times between origins and destinations based on real road

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network data. All system events, including courier logins, order creation, assignment decisions, route execution, and disconnections, are recorded at each simulation step in a PostgreSQL database. This simulation architecture enables systematic evaluation of alternative assignments and routing strategies under realistic spatiotemporal and operational conditions. In addition, it facilitates connections between consumers and distributors through the mediation of a commercial link. Moreover, this virtual platform allows purchases and sales without platform operators intervening considering the stakeholders mentioned below.

User: From the moment a user is connected to the system, the user enters a waiting state a_o before deciding to place an order (a user is associated with an order $o \in O$). When an order is placed, its state changes to an inactive state. In this state, it can evaluate at any time $a_o + t^u$ if the user wants to cancel the order due to, e.g., it takes a long time to be dispatched. If the order is canceled, the application entity removes it from the order queue, and the user is disconnected from the system. In contrast, if the user decides to wait for the order, he or she will wait for the time $a_o + t^u = s^u$, for which the user service time is obtained. After receiving the request, the user is disconnected from the platform. It should be clarified that the application can cancel the order if it determines that it is infeasible to deliver the order to the user due to excess time or cost.

Domiciliary workers: The domiciliary worker is connected to the application at a certain point in time t_c and automatically changes to an active state in expectation of the next event, which determines the course of the simulation. When the notification event is activated, the domiciliary worker can decide whether to accept or reject the order. This event of accepting or rejecting an order is determined by an acceptance rate p_c associated with each domiciliary worker $c \in C$. A domiciliary worker accepts a notification based on probability $P_c = f\left(h_{l_{c,t},l_n}, p_c\right)$, where $h_{l_{c,t},l_n}$ is the haversine distance between the position of the domiciliary worker and the restaurant where the order must be collected ($P_c > 0$). This probability function is inversely proportional to the distance between the domiciliary worker and the restaurant $P_c \propto \frac{1}{h_{l_{c,t},l_n}}$. Indeed, the domiciliary worker tends to reject the order if it is too far from the restaurant. In case of acceptance, the domiciliary worker can start the movement event, which goes to the place to pick up the order, notifying the application once located at the collection site. Once the order is received, the event of moving until the moment of delivering the order is displayed again. Thus, the domiciliary returns to the initial state of activity. When the domiciliary worker decides to reject the order, then it must return immediately to the active state.

On the other hand, domiciliary workers can move around the city freely while in a state of movement, making decisions like those in their active base state. In every fraction of time f_r (fraction of time residual $t/f_r = 0 \; \forall \; t \in T$), the domiciliary worker evaluates whether to reposition. Suppose the position of the domiciliary worker $l_{c,t}, c \in C$ at time $t \in T$ coincides with the action of moving at time $l_{c,t+1} = Movement(l_{c,t})$. In that case, there are two possibilities: the domiciliary worker moves ($l_{c,t+1} \neq l_{c,t}$) or waits in the same place ($l_{c,t+1} = l_{c,t}$). When the domiciliary wants to stop working, the worker could perform the event of disconnecting, whereby the data in the simulation will be collected, i.e., shift time, trips, accepted and rejected orders, and order execution time.

Each domiciliary worker can load a maximum of orders simultaneously due to space and comfort constraints. Each domiciliary worker has a vehicle that alters the mechanics of the movement through the city. Let V be the set of vehicles to which each domiciliary worker $c \in C$ has a vehicle assigned $v \in V$.

Application: The application starts automatically when the simulation begins, entering a constant listening state where all events that are part of the application are orchestrated and interact with the events of the user and the domiciliary workers. Once a user places an order at a place in time a_o, the application activates the event of placing the order at the establishment and subsequently begins to prepare the order with a time d_o. The order enters a queue for evaluation if it can be grouped with another order. While being prepared, it is evaluated whether the order is canceled at a specific time $d_o + t^u \neq s^u$. The application determines, for each order $o \in O$, the total cost of the delivery service. This cost is divided into a base cost plus a variable cost. According to the survey, the base cost is 2.000 COP, and the variable cost depends on distance to the user's position and auction policy, where 50% of the profit that the application receives from a restaurant is used as an incentive for a domiciliary worker to deliver the order.

The auction starts 5 minutes after the user places an order. For each time interval Δf, the event of evaluating grouping is launched. Suppose a domiciliary worker has not accepted the order, then the profit for the worker increases by ten percent ε_o (50% of the order's estimated profit of the order $o \in O$). Once the establishment completes the order, the optimization action is activated, whereby the routing of the order is carried out and the corresponding domiciliary workers are assigned and notified to complete it. Finally, when a domiciliary worker is needed in certain areas, the domiciliary worker is notified to perform prepositioning. This event is launched in time intervals to meet the order demand when there are fewer domiciliary workers. All actions taken within the application, such as stakeholders' characteristics, are ultimately stored in the last control and update event, which triggers the actions in the events of the other entities.

Table 1. Summary of Simulation of Entities

System: Simulation Environment				
Entities	**Attributes**	**Activities**	**Events**	**Variable State**
User	Order	Make and order	Use the app	Customer waiting
			Make the order	
			Cancel the order	
			Wait	Customer dispatched
			Disconnect of the app	
Domiciliary Worker	Vehicle	Evaluate and coordinate	Go to locations	Domiciliary waiting
			Wait	Assigned domiciliary
	Capacity		Pick up order	Domiciliary worker on movement
			Delivery the order	Penalized domiciliary worker
Application	Link	Listen	Receiving order	Received orders
			Send order	Processing orders
			Group order	Delivery orders
		Evaluate	Cancel order	Delivery time
			Create route dispatch	Grouped orders
			Notify users	Domiciliary workers waiting
		Notifications	Notify domiciliary worker	Connected workers
			Replacement of domiciliary worker	Full filled demand
				Unsatisfied demand

Source. Own elaboration.

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Table 1 summarizes the entities that are part of the simulation in this complex system, i.e., three entities that are intertwined through the events that trigger the different actions each can take. The application notifies all potential domiciliary workers of a new order that a user has made, but only one of them can accept the order. The application immediately assigns a route based on one of the MDRP models (Gonzáles, 2021) for the domiciliary worker to collect, said, order, and deliver it to its corresponding user. When the domiciliary worker delivers the order to the user, two things happen simultaneously: the user is disconnected from the application and the domiciliary worker becomes available to accept a new order.

To analyze how different algorithmic decision policies affect operational performance and stakeholder outcomes, the simulation framework implements four distinct assignments and optimization policies to solve the Meal Delivery Routing Problem (MDRP). Each policy reflects a different prioritization of stakeholder goals, ranging from efficiency-driven strategies focused on minimizing delivery times to equity-oriented approaches aimed at balancing workload and income distribution among delivery workers. By evaluating these models under identical demand and supply conditions, the methodology enables a controlled comparison of how alternative assignment logics influence order fulfillment, delivery reliability, and economic performance across stakeholders.

Corporate model: The model enables orders made at the same restaurant to be combined and delivered by a single domiciliary worker in multiple directions, with a maximum of orders, since the capacity of a domiciliary worker's carrying case cannot be exceeded, and the constraints regarding the quality of delivery must be complied with (Reyes *et al*., 2018). Based on this brief introduction, the following mathematical model is proposed:

Notation

C	Set of domiciliary workers for an order $c \in C$
N	Set of nodes $i \in N, N = R \cup C$
$arcs1$	Set of arcs (i, j) $i \in T, j \in C$
$arcs2$	Set of arcs (i, j) $j \in T, i \in C$
$arcs3$	Set of arcs (i, j) $i \in C, j \in C \mid i \neq j$
A	Set of total arcs $A = arcs1 \cup arcs2 \cup arcs3$
S_i	Subset of candidate nodes c to be visited from node $i, i \in N$
$dist_{ij}$	Distance between node $i \in N$ and node $j \in N$
t	Minimum time between delivered orders of the same route
$upper_i$	Maximum arrival time at node $i \in N$
x_{ij}	Binary variable $\begin{Bmatrix} 1 \ \textit{if the domicilary worker passes by } (i \ j) \\ 0 \ \textit{otherwise} \end{Bmatrix}$
y_i	Variable to subtour elimination

Formulation: The illustrated problem can be considered a Multi-Depot Vehicle Routing Problem MDVRP with some modifications. It identifies the optimal set of routes for a fleet of vehicles leaving a depot that must satisfy the demands of a given set of customers—in this case, the locations where orders must be delivered are determined by users. For the case study, this problem must be solved by considering that multiple orders can make up the routes to be generated. All orders come from the same restaurant and have similar preparation times; hence, they can all be collected and delivered by a single domiciliary worker.

$$\min \sum_{i,j \in C} x_{ij} * dist_{ij} + \sum_{i \in T, j \in C} x_{ij} * dist_{ij} \tag{1}$$

Subject to

$$\sum_{i \in S_j} x_{ij} = 1 \qquad \forall j \in C \mid i \neq j \tag{2}$$

$$\sum_{j \in S_i} x_{ij} = 1 \qquad \forall i \in C \mid i \neq j \tag{3}$$

$$\sum_{i \in S_t} x_{it} - \sum_{j \in S_t} x_{tj} = 0 \qquad \forall\, t \in T \mid t \neq i, t \neq j \tag{4}$$

$$y_i + 1 \leq y_j + 3 * (1 - x_{ij}) \qquad \forall\, i \in C,\ j \in C \mid i \neq j \tag{5}$$

$$(upper_i + t) * x_{ij} \leq upper_j \qquad \forall\, i \in N, j \in C \tag{6}$$

$$x_{ij} \in \{1,0\} \qquad \forall\, i,j \in A \tag{7}$$

$$y_i \in \{\mathbb{Z}^+\} \qquad \forall\, i \in C \tag{8}$$

Constraints (2) and (3) ensure that all customers are visited by one of their candidate arcs. Constraint (4) ensures that the balance is met in nodes associated with restaurants. Constraint (5) is responsible for eliminating subtours and defining the maximum number of deliveries within a route, which in this case is three. Finally, constraint (6) ensures that deliveries are ordered according to a time window and that there is a minimum time between the time windows of the deliveries on the same route.

An allocation model is performed to decide which domiciliary worker will take charge of the proposed route:

R	Set of routes $r \in R$
C	Set of domiciliary workers $c \in C$
N	Set of nodes $i \in N$
X_r	Subset of nodes i belonging to the route $r \in R$
V_r	Subset of restaurants belonging to the route $r \in R$
U_r	Subset of customers
W_r	Subset of domiciliary workers d candidates to the route $r \in R$
$arcs\_final_{i,j}$	$= \begin{Bmatrix} 1 \ \ if\ the\ nodes\ i\ and\ j\ belong\ to\ the\ same\ restaurant \\ 0 \ \ Otherwise \end{Bmatrix}$
v_c	Velocity of the domiciliary worker $c \in C$
lb_i	Lower bound of time window of node $i \in N$
ub_i	Upper bound of time window of node $i \in N$
s_i	Service time of the node $i \in N$
$dist_{i,j}$	Distance from node $i \in N$ and node $j \in N$

$disd_{c,t}$	Distance from domiciliary worker $c \in C$ and the restaurant $t \in T$
$x_{c,r}$	$= \begin{Bmatrix} 1 \ \text{if the domiciliary worker } c \text{ is assigned to route } r \\ 0 \ \text{Otherwise} \end{Bmatrix}$
$y_{c,i,r}$	Arrival time of the domiciliary worker c at node i of the route r
z_c	$= \begin{Bmatrix} 1 \ \text{if the domiciliary worker is assigned } c \\ 0 \ \text{Otherwise} \end{Bmatrix}$

Each route has a subset W_r of domiciliary worker candidates to serve it. This subset is defined by the haversine distance between these domiciliary workers and the restaurant fulfilling the orders that make up the route.

$$min \sum_{c \in C} \sum_{r \in R} \sum_{i \in U_r} y_{c,i,r} \tag{9}$$

Subject to

$$y_{c,i,r} \geq lb_i * x_{c,r} \qquad \forall\, r \in R, c \in C, i \in V_r \tag{10}$$

$$y_{c,i,r} \leq ub_i * x_{c,r} \qquad \forall\, r \in R, c \in C, i \in V_r \tag{11}$$

$$y_{c,t,r} = \left(\frac{disd_{c,i}}{v_c} * 3600\right) * x_{c,r} \qquad r \in R, c \in C, t \in V_r \tag{12}$$

$$M * (1 - x_{c,r}) + y_{c,j,r} \geq arcs_{final_{i,j}} \left(y_{c,i,r} + s_i + \frac{dist_{i,j}}{v_c} * 3600\right) \qquad \forall\, c \in C, r \in R, i \in X_r, j \in X_r \tag{13}$$

$$x_{dr} \in \{1,0\} \qquad \forall\, r \in R, d \in W_r \tag{14}$$

$$y_{dir} \in \{\mathbb{R}^+\} \qquad \forall\, r \in R, d \in W_r, i \in X_i \tag{15}$$

$$z_c \in \{1,0\} \qquad \forall\, c \in C \tag{16}$$

Constraints (10) and (11) ensure that domiciliary workers reach restaurants within the time window. Constraint (12) defines the arrival of the domiciliary workers to the restaurant corresponding to the route they are assigned. Finally, constraint (13) defines the arrival of the domiciliary worker to the locations of customers included on the route to which they are assigned. In this model, the objective function ensures that orders arrive at all customers in the shortest possible time. Thus, it minimizes when a domiciliary worker arrives at the customers' nodes. As mentioned above, one of the main objectives of this research is to improve the welfare of all stakeholders. However, this corporate model is mainly focused on meeting the needs of customers, serving as many of them as possible while reducing operating costs without having to account for the welfare of the domiciliary worker fleet. For these reasons, the following model is proposed, where the profits are maximized for all actors involved.

Models focused on domiciliary workers: The proposed model maximizes the number of domiciliary workers where the incomes and workload are balanced; that is, it uses the greatest number of domiciliary workers by eliminating the groupings of orders referred to in the literature as bundles. These bundles result in the number of domiciliary workers being less than the number of orders delivered, since a single domiciliary worker can deliver up to three orders on a single route. Thus, the number of domiciliary workers is maximized since each is assigned only one order. Constraint (5) in the corporate model is altered to create routes with a single order to execute this novel model.

$$y_i + 1 \leq y_j + 1 * (1 - x_{ij}) \qquad \forall\, i \in C,\; j \in C \mid i \neq j \tag{17}$$

Another way to improve the quality of work for domiciliary workers is to assign orders to those who have made the fewest deliveries. However, only some unassigned domiciliary workers can be prospects for an order; only the domiciliary workers at certain distance from the restaurant should be prospects for delivering the order. Hence, the assignment variable can be created $y_{c,i,r}$ for a domiciliary worker $c \in C$ and route $r \in R$. In this case, among those closest to a store, the domiciliary worker with minor orders placed on a given day is selected as follows:

$$min \left(\sum_{c \in C} \sum_{r \in R} \sum_{i \in X_r} y_{c,i,r} \right) + \alpha * \left(\sum_{c \in C} z_c * p_C \right) \tag{18}$$

The objective function (18) has two components. The first refers to the customers and minimizes the arrival time of a domiciliary worker to customers' locations. The second component refers to the domiciliary worker. It minimizes the number of orders made from the beginning of the day (0:00 am), prioritizing domiciliary workers with fewer orders delivered since they logged on to the platform. With the previous considerations, four optimization models for the MDRP are formulated to determine which one benefits all stakeholders the most. These models are considered in the analysis of the results as follows:

Corporate model: The classic MDRP model seeks to minimize the delivery times and costs associated with an order by grouping and fulfilling them in the shortest possible time.

Corporate model no-bundles: The objective of this model is to propose routes with a single order, and each domiciliary worker can only carry one order at a time to minimize the delivery time and cost of each order.

Equal model: The objective is to minimize the allocation time of the domiciliary workers with fewer orders fulfilled to use the largest number of domiciliary workers possible, orders can be grouped using a maximum capacity in the domiciliary workers' bag and arrive as quickly as possible.

Equal model no-bundles: The objective is to propose routes with a single order using different domiciliary workers based on their log on time and minimizing the time they have to wait for orders while trying to minimize the order delivery time.

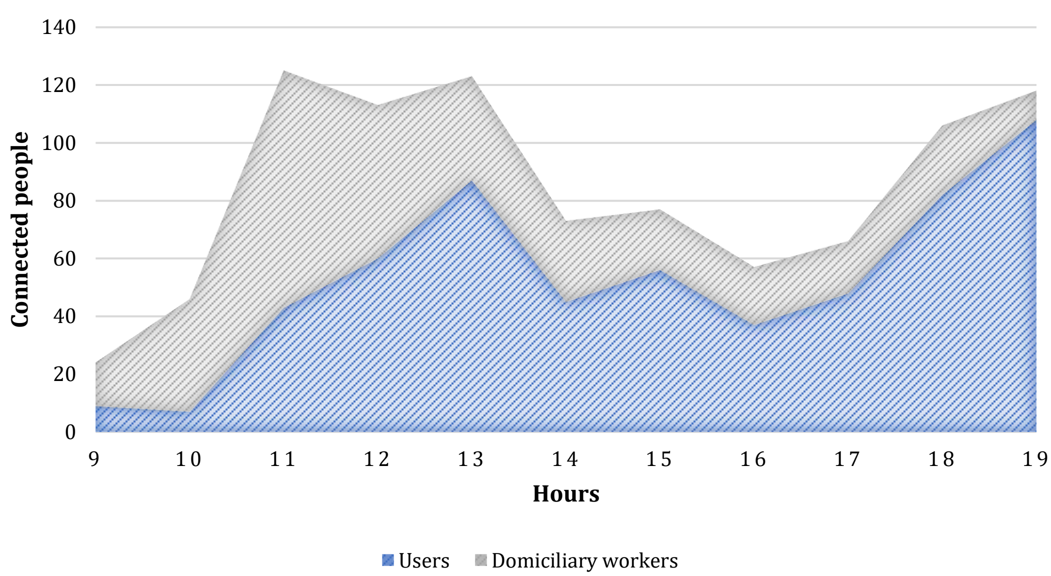
This methodological structure provides the basis for an experimental analysis, in which the proposed optimization models are tested under same conditions to assess their impact on efficiency, equity, and economic performance. Once the simulation is completed, the generated data are consolidated into a set of performance indicators designed to evaluate the impact of each optimization policy on key stakeholder groups.

The indicators capture operational efficiency, service quality, economic outcomes, and labor-related conditions, allowing a comprehensive assessment of how algorithmic decisions affect users, delivery workers, and the platform. Specifically, the metrics include order fulfillment rates, service time, delivery delays, and order acceptance times as measures of user experience and system responsiveness; operational and economic indicators such as platform profit and delivery costs; and courier-related variables reflecting workload and cost exposure. By structuring these metrics within a unified evaluation framework, the methodology enables a managerial interpretation of the trade-offs between efficiency and equity across the proposed optimization models, providing evidence to identify which algorithmic strategy delivers the most balanced value for stakeholders.

4. Computational Experiments and Analysis of Results

Computational experiments were designed to evaluate the performance of alternative order assignments and routing policies within a dynamic on-demand delivery environment. The simulation framework replicates real-time operational conditions, including stochastic demand arrival, heterogeneous domiciliary worker availability, and time-dependent service constraints. The experiments focus on assessing how different assignment strategies influence both operational efficiency and stakeholder-related outcomes, particularly domiciliary worker's work quality, under comparable demand scenarios.

Figure 1. Arrival of Users and Domiciliary Workers per Hour



Source. Own elaboration.

Computational experiments simulate a dynamic on-demand delivery environment in which both user demand and domiciliary worker availability vary throughout the day. As illustrated in Figure 1, domiciliary worker arrivals closely follow the temporal pattern of user demand, particularly during peak hours. This adaptive behavior suggests that domiciliary workers respond strategically to demand intensity to maximize income opportunities and reduce idle time. From a stakeholder perspective, this alignment between demand and labor supply is critical, as it directly affects domiciliary worker earnings, service responsiveness, and overall system stability.

Table 2. Fulfillment Rate of the Users in Instance 4

Optimization model	Orders	Fulfilled orders	Fulfillment rate
Corporate	582	492	84.5%
Corporate-no bundle	582	507	87.1%
Equal	582	522	89.7%
Equal-no bundle	582	526	90.4%

Source. Own elaboration.

Fulfillment rate is not merely a performance KPI; it is a systemic health indicator with cascading implications across stakeholder domains. For customers, each unfulfilled order constitutes a direct service failure, losing trust, and triggering negative reviews that damage brand equity. For domiciliary workers, low fulfillment correlates strongly with income instability and algorithmic deactivation risk: platforms often interpret repeated unfulfilled orders as evidence of poor performance, triggering penalties without appeal mechanisms. For the platforms themselves, the fulfillment rate governs economics: each unfulfilled order represents not only lost gross merchandise value but also wasted infrastructure investment in dispatch logistics, real-time tracking, and customer support overhead. Based on that Table 2 reported the fulfilment rate of all models, for instance **Sfour**. While all models achieve relatively high fulfillment levels (above 84%), the Equal-based models outperform the corporate approaches, reaching fulfillment rates of 89.7% and 90.4%, respectively. This improvement suggests that assignment strategies emphasizing balanced domiciliary worker participation increase the likelihood of prompt order acceptance, thereby improving system reliability.

Table 3. Obtained Money from an Operation Day of the Application Based on the Optimization Model for Instance 4

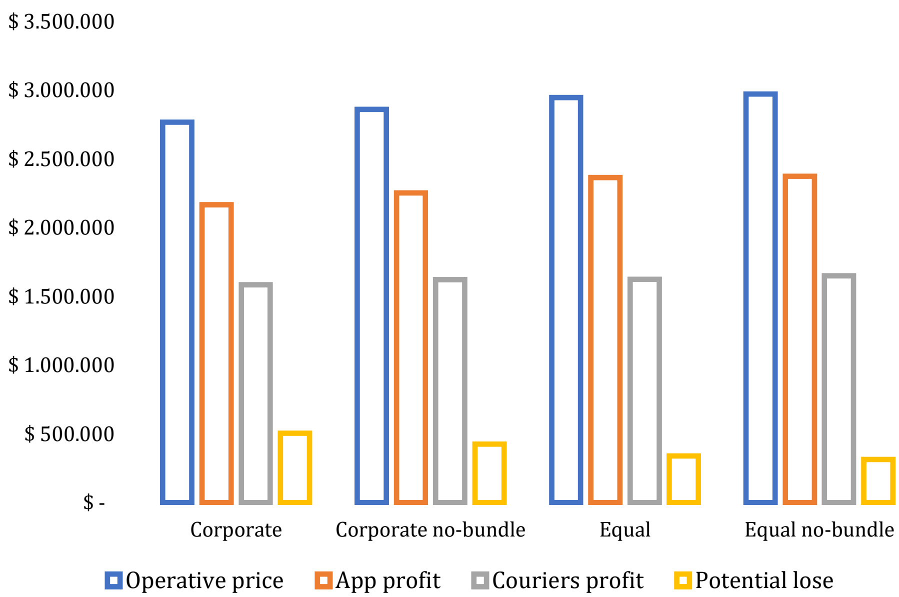
Comparison of productivity						
Optimization model	**Incomes**	**Application profit**	**Potential loses**	**Complete orders**	**Domiciliary workers available**	**Used domiciliary workers**
Corporate	$ 2,769,052	$ 2,166,846	$ 505,723	492	415	241
Corporate no-bundle	$ 2,861,366	$ 2,253,160	$ 424,802	507	415	254
Equal	$ 2,946,780	$ 2,366,156	$ 339,388	522	415	255
Equal no-bundle	$ 2,973,147	$ 2,375,060	$ 313,021	526	415	246

Source. Own elaboration.

When time-based metrics are comparable, economic performance becomes a decisive factor in evaluating assignment policies. Table 3 summarizes the financial outcomes generated by each optimization model during a full operational day. The results show that the Equal and Equal-no bundle models generate the highest total revenue and platform profits, reaching COP 2,946,780 and COP 2,973,147, respectively. Compared with the Corporate model, the Equal-no bundle approach increases platform profits by approximately 10.5%. This indicates that allocation policies oriented towards equitable distribution of orders among couriers can generate superior financial outcomes compared to corporate-priority approaches.

In addition to higher profits, equity-oriented models substantially reduce potential losses associated with uncompleted orders. While the Corporate model shows potential losses of COP 505,723, the Equal-no bundle model reduces this figure to COP 313,021, representing a reduction of approximately 38%. This improvement is driven by higher order completion rates and more efficient utilization of available domiciliary workers.

Figure 4. Generated Profit for the Application per Day



Source. Own elaboration.

Figure 4 illustrates the distribution of operational revenue among stakeholders, the idea is to understand who is the distribution of incomes for each stakeholder, the total sales prices of the total orders (operative price), the amount of profit obtained for the app (app profit), the incomes obtained for all the domiciliary workers (couriers profit) and, at least, the incomes the stake holders do not obtain because the order was not accepted (potential lose). The results indicate that fair assignment models not only enhance platform profitability but also improve average earnings for domiciliary workers, with an estimated average gain of COP 3,137.05 per day. This suggests that balancing workload across a broader set of domiciliary workers can simultaneously increase total system productivity and individual income opportunities.

Taken together, the results reveal that equity-oriented assignment policies introduce favorable trade-offs between operational efficiency and stakeholder welfare. While Corporate models slightly outperform others in delivery delay variability, Equal-based models achieve higher fulfillment rates, lower potential losses, and superior economic outcomes without substantially degrading service quality. These findings show that algorithmic assignment rules play a strategic role in shaping how value and risk are distributed across stakeholders.

From a Latin American perspective, where platform work is often a primary income source and institutional labor protections remain limited. In such environments, algorithmic policies that worsen income instability may intensify existing labor vulnerabilities. The observed reduction in potential losses and improved profit distribution under equity-oriented models suggest that algorithmic governance can serve as a strategic lever to enhance both economic performance and social sustainability.

5. Concluding Remarks

This paper proposes a two-stage simulation optimization model that is proposed to solve and analyze the order allocation problem within the context of a Colombian application. Different changes are proposed for the order allocation model focused on improving the well-being of the domiciliary workers responsible for placing the orders. Among the proposed changes are making a fair allocation of delivery addresses, maximizing the use of used delivery addresses, and prioritizing the delivery addresses for minor requests. The analysis presents the impact of the auction system for the assignment of an order and the system of conformation of combo orders (Bundles).

The results obtained from the computational experiments highlight that algorithmic design choices in on-demand delivery platforms extend beyond technical efficiency considerations and function as mechanisms of stakeholder governance. Consistent with prior research on algorithmic management, the findings show that assignment policies shape not only system performance but also economic opportunities. In this study, equity-oriented models reduce workload concentration and income volatility while preserving delivery reliability, demonstrating that efficiency and fairness are not mutually exclusive goals.

The fair allocation constraints of the proposed model affect the allocation performance since it forces domiciliary workers who are not considered a priori to be taken into account (these workers have a great capacity to deliver homes in the fastest way possible). Indeed, the efficiency of the fleet used to deliver and dispatch orders is impaired. However, it reflects positively on the profits generated by domiciliary workers on the platform by 10.5%, reduces the potential loss due to unfulfilled deliveries by 38% (increasing business income directly), and directly increases the level of user satisfaction when being served. When comparing the corporate model without a bundle with the fair corporate model without a bundle, it is found that the percentage of orders outside the time window increases by 11%, and the average arrival time of orders shows an increase of 24% (around two minutes).

The relevance of these findings is particularly significant in Latin America, where delivery applications run within environments characterized by labor informality, limited social protection, and high competition among domiciliary workers. In such contexts, algorithmic policies that worsen workload concentration and income uncertainty can intensify existing vulnerabilities. The results of this study suggest that platform designers can use algorithmic adjustments as a practical tool to mitigate these challenges while preserving competitive performance.

Future work can focus on developing and exploiting new and exclusive policies for each stakeholder so that the profits can be balanced between the application and domiciliary workers. Integrating operating policies to individually recognize the profits of the application and the households associated with rigorous service quality standards can significantly benefit the platform's operation. Lastly, when restaurants are modeled as actors representing their impact on operations, service quality is strongly affected, and it is difficult to monitor it from the application. Restaurants have their own policies and depend on external variables that affect the platform’s operation.

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